HUMAN APPROPRIATION OF NET PRIMARY PRODUCTIVITY (HANPP) IN TEXAS: A STATEWIDE ANALYSIS OF SUSTAINABILITY IN THE AGRICULTURAL AND TIMBER SECTORS

A Thesis

by

CHRISTOPHER P. GRAFF

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2009

Major Subject: Geography

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Approved by:

Chair of Committee,	Andrew Millington
Committee Members,	Anthony Filippi
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ABSTRACT

Human Appropriation of Net Primary Productivity (HANPP) in Texas:

A Statewide Analysis of Sustainability in the Agricultural and Timber Sectors.

(May 2009)

Christopher P. Graff, B.S., Clark University

Chair of Advisory Committee: Dr. Andrew Millington

The sustainability of the Texas agricultural and timber sectors is measured using the ratio of human appropriation of net primary productivity (HANPP) to available net primary productivity (NPP) on a county-by-county basis for the entire state. By combining NPP and HANPP, a measure of ecologic sustainability in terms of carbon dynamics is achieved. This is based on a six-year average from 2000 to 2005 obtained from the NASA MODIS sensor, as well as the calculated NPP harvested from agricultural and timber activities reported by USDA Agricultural and Texas Forest Department timber statistics covering the same years.

The spatial pattern of NPP in Texas is strongly influenced by moisture availability and is naturally highest in the Gulf Coastal Plains, and parts of east Texas. Areas of artificially-high NPP can often rival or surpass naturally occurring NPP and occur primarily due to irrigation, such as in the Panhandle and lower Rio Grande Valley. Human appropriation of this carbon is greatest in the Panhandle and lower Rio Grande Valley where, in many counties, >45% of all carbon produced is appropriated. HANPP values throughout the rest of the state are moderate (10-24%) corresponding well with global and national HANPP literature. These results support two conflicting findings: increased HANPP indicates decreased ecological sustainability, but is also a measure of increased agricultural efficiency.

ACKNOWLEDGEMENTS

I would like to thank my committee chair, Dr. Millington and his persistent “Any progress yet?” e-mails, as well as my committee members, Dr. Filippi, and Dr. Jones, for their guidance, support, and drive throughout the course of this research.

Thanks also go to my wife and family for their incessant nagging to keep writing, without which I would still be on page one.

NOMENCLATURE

ε	Light Utilization Efficiency
fAPAR	Fraction of Available Photosynthetically-Active Radiation
GPP	Gross Primary Productivity
HANPP	Human Appropriation on Net Primary Productivity
HI	Harvest Index
NPP	Net Primary Productivity
NPP_O	Potential NPP
NPP_{act}	Actual NPP
$NPP_{aquatic}$	Aquatic NPP
NPP_h	Harvested NPP

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CHAPTER I

INTRODUCTION

This research presents estimates of net primary productivity (NPP) and human appropriation of net primary productivity (HANPP) for the state of Texas on a county-by-county basis. In doing so it seeks to evaluate the sustainability, in terms of carbon, in the agricultural and timber sectors of the state's economy. This makes it one of only a limited few studies worldwide to provide spatially-explicit estimates of HANPP. Furthermore it offers the first extensive look at HANPP anywhere in the United States at the county-level, as well as the first set of estimates for Texas. This research offers a robust method to digest agricultural and forestry statistics for carbon budgeting and assessing sustainability.

The concept of human sustainability, especially in relation to manipulating our environment, is covered by a well-developed discourse which extends back to the mid-1800s (Lambin et al. 2001; Marsh 1864; Sauer 1956). Whilst it provides many examples of unsustainable and a few sustainable uses, quantifying sustainability has, until recently, been rather elusive and still generates debate (Bell and Morse 2003). Of great importance to Texas is the sustainability of its agricultural and timber sectors because of the high number of workers in these sectors. According to 2002 statistics, 25.9 percent of the state's 1.0-1.5 million rural jobs were in the agricultural sector and 12.9 percent of

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This thesis follows the style of *Professional Geographer*.

approximately 11 million urban jobs were also in this sector (USDA (Bureau of Economic Research) 2007). Similarly forestry is a $21 billion-a-year industry (Mt Joy 2005). Sustainability of agriculture and forestry can be approached by considering inputs (e.g., agrochemicals, irrigation water, capital investments) and comparing these to various types of outputs (Haberl 2001a, 2001b). However, a more fundamental way of considering sustainability in these sectors is to reduce the inputs and outputs to a fundamental building block of life on Earth – carbon. In this vein Haberl et al. (2004) argue that through an understanding of net primary productivity (NPP) a society can evaluate both its own sustainability as well as that of other species. In particular, research by Vitousek et al. (1986) has developed the concept of human appropriation of net primary productivity (HANPP) which comprises both understanding and measuring of NPP and society's consumption or alteration of it.

Most studies calculate HANPP from single (global) values for each parameter modeled, making them spatially independent and giving no indication of spatial variability in HANPP. This leaves simple questions such as 'where is human appropriation greatest?', and 'where is it changing most rapidly?' unanswered. Methodological complexities and data availability have hampered the production of spatially-explicit HANPP estimates. Only a few have been able to compute HANPP spatially but they are either narrowly focused (Haberl et al. 2001) or at national scales and fraught with biases (Imhoff et al. 2004). Because the implications of this research for sustainability, as well as the recent attention to carbon accreditation, knowing the carbon dynamics and productivity of agricultural and timber industries for Texas is both necessary and, potentially, economically relevant.

The methods employed in this research convert agriculture and timber censuses into carbon as well as calculate actual NPP through remote sensing. It then compares the two as the amount present and the amount appropriated by humans. The result is HANPP or the percentage of carbon removed, consumed, or otherwise manipulated for human interests.

Net Primary Productivity

The concept of primary productivity and how it is measured evolved as a means to quantify the energy (carbon) fixed by plants (Lieth 1973). Gross primary productivity (GPP) is the product of photosynthesis, and is measured through available solar radiation, exposed leaf area, and plant light-use efficiency (Gower, Kucharik, and Norman 1999). Because GPP does not account for normal plant respiration, net primary productivity (NPP) is used. NPP is GPP minus autotrophic respiration and can be thought of as the average amount of carbon fixed within an area over a specified period of time (Sharpe 1975). Understanding the dynamics of fixing carbon through NPP has been shown to be important in assessing sustainability (Haberl 2006; Krausmann 2004; Vitousek et al. 1986).

Carbon is the primary source of life on our planet. Ourselves, along with almost all other species rely on it for food, fuel, and shelter. Furthermore NPP represents one of the most accessible measurements of the carbon cycle (Zheng, Prince, and Wright 2003:46). Through NPP we gain an understanding of the flow of energy within local systems as well as global systems. Therefore, as a measure of solar energy, converted through photosynthesis into chemical energy, NPP represents what energy is available in an area (actual NPP), but can also be used as a measure of the amount of energy co-opted by humans and consumed or moved out of the area. This not only explains what is available but how humans are influencing and changing the carbon cycle.

The above-ground portion of NPP (ANPP) is easily the most studied and best understood as it is the most accessible. It is produced through photosynthesizing leaves. We therefore need to understand how solar energy interacts with leaves, how efficient those leaves are at turning solar energy into chemical energy, and then what happens to this chemical energy. The below-ground portion of NPP (BNPP) is poorly understood, difficult to measure, and therefore is usually only estimated or recycled within the NPP literature (Gill et al. 2002; Prince et al. 2001; Vitousek et al. 1986).

To calculate NPP one must know how much energy is entering the system and how efficient different plants are at photosynthesizing that energy. The fraction of absorbable photosynthetically-active radiation (fAPAR), or the term measuring available light, is influenced by where the place being studied is located and the time of day and year.

Obviously the time of day as well as year affect the amount of incoming solar radiation. Similarly latitude affects this amount; latitudes closer to the poles being least productive (Schloss et al. 1999). Calculating fAPAR is based on the difference between photosynthetically-active radiation (PAR) entering a canopy and PAR reflected back up into the canopy, and is often based on an upper layer and lower layer to the canopy (Gower, Kucharik, and Norman 1999:36):

$$fAPAR = \frac{[upper(PAR_a - PAR_b) - lower(PAR_a - PAR_b)]}{PAR_a} \qquad \text{(1) fAPAR}$$

where PAR_a is incident on a vegetation canopy and PAR_b is reflected upward from the ground. A common error here is that PAR is often only calculated at a single point in time where long-term averages may be more accurate. Also because the solar zenith angle plays a large role in the amount of PAR entering, and being refracted within a vegetation canopy, measuring canopy gaps becomes important.

A leaf area index (LAI) is used to quantify the density of a canopy exposed to PAR. LAI is important not only as a measure of exposed leaves but also because it has a strong influence on the fluctuation of water vapor and carbon dioxide within the ecosystem (Gower, Kucharik, and Norman 1999:30). LAI can be measured both directly and indirectly. Direct measures include harvested data, using allometrics applied to tree diameter data, or measuring leaf litter fall (Gower, Kucharik, and Norman 1999:30). Indirect measures use light-sensitive instruments to measure radiation transmitted through vegetation. According to Gower, Kucharik, and Norman (1999:36), once adjusted for non-photosynthetic material (e.g. stems and branches) as well as using an appropriate sampling size, indirect measures compare well with the direct measures of LAI.

The PAR that reaches the leaves, fAPAR, is converted through photosynthesis into chemical energy that is consumed as biomass. A plant's ability to convert fAPAR into biomass is represented by the term: ε, or its conversion efficiency. ε is commonly available in the literature, or can be derived statistically with ecological models, but independently calculated biome values tend to predict more reliable values (Ruimy, Saugier, and Dedieu 1994:5275). Efficiency is not only dependent on the species but also on the condition of the environment it inhabits. In general NPP increases from cold to warm and from dry to moist (Schloss et al. 1999:18).

When examining the relationships between NPP, fAPAR, and ε using a variety of NPP models, Ruimy et al. (1999) show that local variations in NPP are primarily due to variations in fAPAR; but at a global level variations between NPP and fAPAR do not correspond well, and neither does NPP and ε. The authors explain these variations in NPP being controlled firstly by fAPAR, and secondly by the different definitions of, and methods used to calculate ε. They found that spatial variations in NPP were represented by variations in fAPAR, while magnitude differences in NPP were influenced by variations in ε (Ruimy et al. 1999:64).

Potential and Actual NPP

The HANPP literature makes a clear distinction between potential and actual NPP. Actual NPP is the current net primary productivity, i.e. the amount of energy fixed during a specified amount of time. Potential NPP differs because it tries to estimate NPP in an environment void of human influence; often termed pre-human impact (Haberl, Erb, and Krausmann 2007). In calculating potential NPP one seeks a measure of carbon in an ecosystem as if there was no human impact. In this way by comparing potential NPP and actual NPP, all production that is appropriated is accounted for, with no human activities being omitted.

Unfortunately calculating potential NPP is very difficult since there are very few environments that can truly be said not to have been influenced by human activities. This is because human actions are global, affecting temperature, precipitation, and soil conditions; all of which are used as inputs to calculate a pre-human impact vegetation regime (Vitousek et al. 1986; Wright 1990).

This study takes a different approach to the above, commonly-used, approach by using actual NPP calculated from MODIS satellite imagery. The MODIS product used here derives NPP from a real point in time; therefore actual human-induced land-cover changes are embedded in the imagery. The rationale in using actual NPP is twofold. First, this study considers a short period of time – six years – in an already highly developed society. Therefore it assumes human-induced changes in land-cover are of minor consequence during the six year time span. Secondly, the goal of this research is to evaluate the sustainability of the modern agriculture and timber industries in terms of carbon appropriation in Texas. Consequently, there is little relevance in knowing how much carbon was sequestered pre-human impact.

Human Appropriation of Net Primary Productivity

HANPP compares estimates of NPP to that which humans either consume, replace or otherwise manipulate (Vitousek et al. 1986, 368). It is an energy balance between what is present (or would be present) and what humans appropriate. HANPP, then, speaks directly to the human sustainability literature. Research has focused on how HANPP has changed throughout human development (Giampietro, Bukkens, and Pimentel 1992; Haberl 2006), and on current rates and sustainability issues (Wackernagel et al. 2002). Through the work of Giampietro, Bukkens, and Pimentel (1992), who evaluated HANPP for hunter-gatherer, agrarian, and industrialized societies, it is clear that HANPP is a powerful model of human energy consumption. Historical analysis of HANPP also benefits the contemporary view by providing trajectories for modeling sustainability futures. Haberl (2006) predicted that by 2050 human-controlled energy inputs will account for over 50% of global NPP and Tilman et al. (2001, 281) argue that agricultural demand will become so great that the impact will lead to "… unprecedented ecosystem simplification, loss of ecosystem services, and species extinctions."

HANPP not only explains what is available (implying our sustainability as well as other species) but how humans are influencing and changing the global carbon cycle. As mentioned previously there are several human activities that appropriate NPP, the main ones being land-cover change, harvesting primary productivity (plants) and harvesting secondary production (livestock). HANPP is therefore the difference between an ecosystem's potential NPP (NPP_O) and both actual NPP (NPP_{act}) and harvested NPP (NPP_h).

$$HANPP = NPP_O - (NPP_{act} + NPP_h) \qquad \text{(2) Conceptual HANPP}$$

The difference between NPP_O and NPP_{act} accounts for changes in land-cover, while NPP_h accounts for NPP harvested for human consumption. Potential NPP is usually modeled based on two controlling variables: precipitation and temperature. Remote sensing products such as MOD17 from MODIS can very accurately derive actual NPP, and therefore have embedded in them changes in NPP from land-use and land-cover (Heinsch et al. 2003). After removing that percent which is harvested for human use, what remains is HANPP.

Land-Cover Change

As Lepers et al. (2005) make abundantly clear, we do not know enough about rapid land-cover change. Though there is not enough room here, suffice it to say there are many drivers acting at many scales and in increasingly diverse and convoluted pathways that result in land-use and land-cover change (LUCC). In the HANPP literature, as in most

LUCC literature, two types of conversion garner the greatest attention. First is the conversion from forest to another land-cover (e.g. agriculture). The potential to sequester large amounts of carbon is severely diminished when forests are converted to other land-cover types. In the past HANPP studies saw this conversion as detrimental to carbon sequestration but a recent study questions this (Hicke et al. 2002). Due to intense management and ever increasing supplements, agricultural land is able to compete with and in some areas fix greater amounts of carbon than local forested land. Though such practices may be positive in terms of carbon budgets there are concerns for other biogeochemical cycles.

The second major impact of land-cover change on NPP appropriation is conversion to urban land-cover types. This is especially of concern when urban growth expands onto the most productive lands (Alphan 2003). The result is quite dramatic as NPP can drop to zero. Roadways replacing vegetation (Wright 1990), and urban sprawl replacing wetlands (Cardoch, Day, and Ibanez 2002) are prime examples. There is still an intense debate on the productivity of urban gardens and manicured lawns in producing similar amounts of NPP as native vegetation (Robbins and Sharp 2003; Robbins and Birkenholtz 2003).

Harvest

All of our food, and a large percent of clothing and shelter, is appropriated through harvest and therefore offers a direct means to measure HANPP. Harvest can be broken into two groups: primary producers and secondary producers (Whittaker 1975). Harvest of primary producers (i.e. crops and timber) has been central to HANPP studies as they represent the basic unit of extraction. Based on robust equations, crop data can be converted to NPP (Lobell et al. 2002). Conversion becomes slightly more complicated when converting timber harvest data to NPP since most measures of NPP are annual while forests take many years to reach maturity. The carbon tied up in forests is therefore on a much longer temporal scale than standard NPP measurements and must be accounted for properly (Krausmann 2001).

Quantifying the appropriation of NPP from secondary producers (livestock) is more difficult than primary producers and therefore receives less attention in the literature (Imhoff et al. 2004; Rojstaczer, Sterling, and Moore 2001). The conversion of harvested meat or animal byproducts (e.g. eggs, milk, wool) back to primary productivity is difficult given the diversity of diets. NPP varies widely between crop types, as well as pasture and hay, and therefore for accurate measurements each crop composing a particular animal's diet must be considered separately (Imhoff et al. 2004). Furthermore double counting of primary productivity is of great concern. Some animal feed is imported and therefore needs to be added to the equation while other feeds may be grown locally and must not be double counted as both livestock production and crop harvest. Because of the difficulties posed by these issues secondary production has only been dealt with spatially at coarse scales (Imhoff et al. 2004) or aspatially (Wright 1990).

Study Area

The state of Texas was chosen for the abundant wealth of existing datasets relating to agricultural and timber production, as well as statistics on human population and activities. An abundance of detail-specific data affords this study a finer resolution leading to a greater understanding of each activity's impact on appropriation.

As agriculture is a well-developed business in the USA and a strong agricultural economy is important to the nation, crop production data at a variety of spatial scales is readily available. USDA agricultural censuses, although for agro-economic purposes, represent a great wealth of data for sustainability studies, specifically HANPP. Many studies are now looking at the harvest data in order to assess NPP in agriculturally-dominated regions (Hicke, Lobell, and Asner 2004; Lobell et al. 2002; Prince et al. 2001), but have yet to be applied to HANPP.

Secondly, Texas offers an interesting suite of ecological and agricultural/ timber regions for evaluating NPP and HANPP. Texas has several distinctly diverse regions where specific activities excel and others are simply impossible. Because each of these zones has such distinct environments (Figure 1) different agricultural activities are present that may not be found elsewhere in the state. Examples include the Piney Woods and its timber industry in east Texas, rice along the coast, and citrus in the lower Rio Grande Valley.

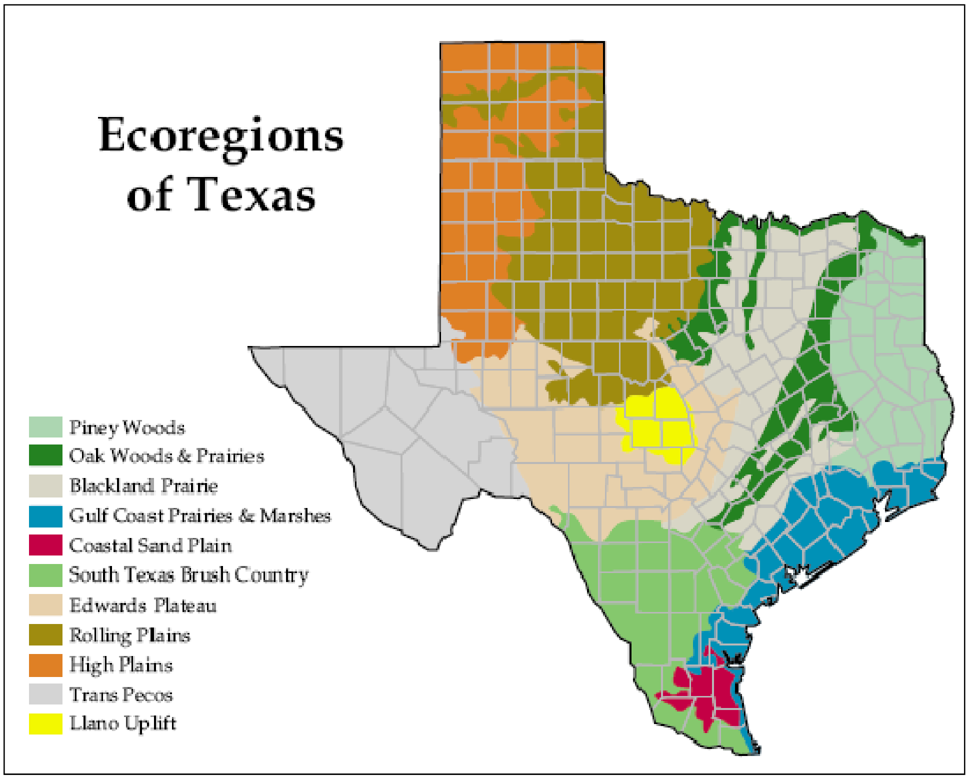


Figure 1: Texas Ecoregions (Griffith et al. 2004).

Texas ecoregions can easily be classified along a southeast to northwest gradient. This gradient is driven by both temperature and precipitation, and places natural boundaries on potential NPP (Schloss et al. 1999). The Gulf Coast Prairies and Marshes are characterized by high productivity, both natural and agricultural. Timber is dominant in the Piney Woods of east Texas due to abundant forest resources. Central Texas receives moderate temperatures and rainfall, each controlling limits of naturally occurring NPP. The High Plains in the Panhandle offer shorter growing seasons due to temperature limitations; approximately 5-10°C less than the Gulf Coast Regions (National Oceanic and Atmospheric Administration 2008). In west Texas NPP is limited by water availability without human intervention.

It should be noted that although ecoregions set natural limits on NPP, human management practices can greatly out-produce an area's natural potential (Prince et al. 2001:1202). Most importantly to Texas agriculture is the use of irrigation from aquifers (the Ogallala in the panhandle and the Edwards in central Texas).

Finally a comparison can be made between Texas and Austria. Much of the leading HANPP work has been conducted in Austria due to a lengthy historical agriculture data. Studies range from basic replications of Vitousek et al.'s seminal 1986 work (Haberl 1997) to more advanced, spatially-explicit work (Haberl et al. 2001) and show both breadth as well as depth in understanding the role of human appropriation in Austria. Texas and Austria are roughly equal in area and are both highly developed with a large number of economic activities utilizing natural resources. Furthermore they both have a wide variety of harvesting activities, some similar while others are quite different. Studies of Texas and Austria are then complementary and through comparisons offer significant gains in understanding the role of HANPP in human sustainability.

Study Period

To be of contemporary relevance this study looks at HANPP in this decade. Data is readily available annually from 2000 to 2005. Using this time period is important to facilitate a dialog with sustainability studies as well as the political and economic efforts toward carbon balancing through credit programs such as the North American Carbon Program (NACP) (Hicke and Lobell 2004).

Data averaging was used to normalize the six-year time frame, thereby correcting short-term variability in both climate and agro-economic fluctuations (Imhoff et al. 2004:872). For example, any particularly poor harvests or exceptional harvests, due to either environmental or economic drivers, could be moderated by using the averaged data. Furthermore not all datasets are complete at the county-level for every year. An average attenuates any sudden drops if reported statistics are missing for a particular year. The resulting datasets therefore offer a robust, albeit somewhat conservative, baseline for HANNP during the early 21st century.

Research Structure

The following chapter situates this research within the HANPP literature by drawing methods from the geographic, ecological, and agricultural literatures. It details how this body of knowledge has developed and attempts to place this study as an advancement in techniques. These techniques are detailed in Chapter III: Methods. The chapter begins with an overview of the methods and in subsequent sections details the image processing (NPP_{act}), agricultural and timber statistic processing (NPP_h), and finally integration of the two parts (HANPP). Chapter IV discusses the research findings generally for Texas as well as specifically for each major harvest activity. Chapter V analyzes the results. It seeks to explain some of the major patterns of NPP_{act} and NPP_h as they relate to human appropriation. Finally, Chapter VI: Conclusion offers some final remarks on these methods for estimating HANPP, as well as the sustainability of agricultural and timber industries in Texas.

CHAPTER II

LITERATURE REVIEW

The study of human appropriation of net primary productivity (HANPP) is comprised of two parts: understanding and measuring net primary productivity (NPP) and understanding and measuring human's consumption or alteration of NPP. This chapter begins by exploring our understanding of NPP and the evolution of methods used to measure it. The second half is dedicated to the methods used in estimating human appropriation of NPP.

Net Primary Productivity

The concept of human sustainability, especially in relation to manipulating our environment, has a deep and well-developed discourse (Lambin et al. 2001; Marsh 1864; Sauer 1956). Within this vein the concept of primary productivity and how it is measured has evolved as a means to quantify the energy (carbon) fixed in plant matter (Lieth 1973). Through an understanding of NPP one can evaluate both our sustainability as well as that of other species (Haberl, Schulz et al. 2004). Primary productivity is the product of photosynthesis. It is measured through available solar radiation, exposed leaf area, and plant light-use efficiency (Gower, Kucharik, and Norman 1999). Because this gross primary productivity (GPP) does not account for normal plant respiration net primary productivity is used. Net primary productivity (NPP) is gross primary productivity minus autotrophic respiration. It is the average amount of carbon fixed within an area over a specified period of time, commonly a year (Sharpe 1975). Understanding the dynamics of fixing carbon (NPP) has been shown to be of utmost importance when assessing sustainability (Haberl 2006; Krausmann 2004; Vitousek et al. 1986).

Both moisture and temperature are the dominant natural controls for NPP (Nemani et al. 2003; Ruimy, Saugier, and Dedieu 1994; Schloss et al. 1999). Moisture availability places boundaries on the productivity of plants (Churkina, Running, and Schloss 1999; Schloss et al. 1999). Both the lack of, or over-abundance of moisture can constrain plant growth. Temperature too places physical controls of biota. It has been shown to be strongly correlated with the quantity of biomass as well as conversion efficiencies (Box, Holben, and Kalb 1989; Kimball et al. 2006). In Texas there is therefore a strong north-south gradient controlled by temperature and an east-west gradient controlled by moisture. Available solar radiation also controls NPP. Nemani et al. (2003) illustrated this by correlating how a decrease in Amazonian cloud cover in the past 18 years has yielded a 42% increase in global NPP. They argue that there is more incoming solar radiation for tropical plants to absorb and convert to carbon.

Methods for measuring NPP range from general biome estimations (Vitousek et al. 1986), complex conversion of vegetation statistics (Lobell et al. 2002), sophisticated remote sensing algorithms (Running et al. 2004), and modeled biogeophysical processes (Cramer and Field 1999; Cramer et al. 1999). Each method implements different types of data in an attempt to model NPP. They each have their own sets of obstacles and biases to overcome as will be discussed in subsequent sections.

Lieth (1973:310) has illustrated the wide range of historical global values for NPP, ranging from 13 to 164 Pg of carbon. Recent attempts to quantify NPP still vary due to errors in both data and methods (Rojstaczer, Sterling, and Moore 2001), but consistently range from 40 to 80 Pg (Cramer et al. 1999). Focusing on defining and understanding individual biomes has gone a long way in refining these NPP measurements (Kicklighter et al. 1999; Turner et al. 2006).

Aquatic NPP

Although the great majority of research in NPP has focused on terrestrial NPP it is import to recognize the work in aquatic NPP. This work is less focused on carbon sequestration and more on modes of transportation (Duarte and Cebrian 1996). Within this body of work calculating total aquatic net primary productivity ($NPP_{aquatic}$) is less important and therefore estimations tend to be a side note.

There are three main differences between measuring aquatic and terrestrial variables:

i. Methodologies to measure variables,
ii. Accelerated turnover rates, and
iii. The accelerated transportation of material.

Physically collecting measurements of primary productivity throughout the ocean used to be the only reliable method; see Peterson (1980). Carbon was measured with a radiocarbon tracer method, $^{14}C\text{-}CO_2$, where dissolved inorganic carbon was measured as it was taken up by planktonic algae (Peterson 1980:360). His results supported the claim that oceans produce around a half of the total global NPP estimate. The introduction of remote sensing produced new methods and attempts to combine both terrestrial NPP and $NPP_{aquatic}$. As an example Field et al. (1998) modeled both terrestrial and $NPP_{aquatic}$ from satellite data. By their estimates aquatic and terrestrial systems produce about equal amounts of NPP. Muller-Karger et al. (2005) were also able to successfully use satellite imagery to develop NPP variables although they concentrated specifically on continental shelf margins.

Turnover rates are dramatically different between aquatic and terrestrial systems. Terrestrial turnover is roughly 19 years while in aquatic systems the rate is 2-6 days (Field et al. 1998:238). This rate means that photosynthesis and respiration are happening quickly, and a single snapshot of the system is more robust than in terrestrial systems. This consistent turnover also helps keep ocean NPP rather stable across seasons, while terrestrial seasonal variations remain high. Also, while aquatic biomass is high, NPP will remain rather low (remember that NPP is the difference between photosynthesis and respiration). In fact Field et al. (1998:238) found that aquatic primary producers only account for 0.2% of total global primary producers.

Finally the transport, and according to Duarte and Cebrian (1996), ‘fate’ of all this carbon is extremely important in aquatic systems. Another way to compartmentalize $NPP_{aquatic}$ is:

$$NPP = D + H + E + S \tag{3) NPP_{aquatic}$$

where D is decomposed carbon, H is consumed by herbivores, E is exported out of the system and S remains for the potential of storage (Duarte and Cebrian 1996:1759). Duarte and Cebrian found different rates between species, plant types, and locations. The majority of carbon (90%) was produced in the open ocean by unicellular autotrophs. The next largest producers are macrophytes (such as sea grasses, marsh plants, and mangroves) in coastal systems (Duarte and Cebrian 1996:1758). Important among their findings was that the storage of NPP was independent of total production and instead dependant on plant structure (i.e. macrophytes taking longer to decompose and therefore sequestering more carbon) and environmental conditions. Muller-Karger et al. (2005) reached a similar conclusion by studying transport interactions on continental shelves.

Major Model Comparisons

The year 1999 saw two separate journals: *Global Change Biology* and *Remote Sensing of Environment,* release special issues evaluating modern methods used to measure NPP, and in particular terrestrial NPP (Cohen and Justice 1999; Cramer et al. 1999). These special issues offer an appropriate point to begin understanding the modern techniques used to model NPP. There are two main approaches to modeling NPP, as well as a third minor approach (Cramer et al. 1999). The first uses remote sensing products such as MODIS or AVHRR to inform models. The second simulates carbon dynamics based on defined vegetation structures and the third simulates both carbon dynamics as well as vegetation structure.

The purposes of these special issues was to collectively present what techniques are being used to simulate NPP, how they both agree and disagree, and what questions still remain unanswered. Cramer et al. (1999) described the evolution of modeling NPP beginning with Lieth's (1975) MIAMI model which used regressions to estimate NPP and then how the aforementioned methods evolved to empirically model many of Lieth's assumptions. Remote sensing has allowed researchers to model actual, spatially-discrete climatic variables. Simulating carbon dynamics between vegetation structures is useful in describing carbon fluxes between vegetation types but fails to account for the spatial redistribution of vegetation (Cramer et al. 1999:5). The third group simulates both carbon dynamics and vegetation structure but has only been applied to potential vegetation and not actual (Cramer et al. 1999:5).

These articles focus on key variables used to model NPP. Gower et al. (1999) looked at methods to measure absorbed photosynthetically-active radiation (APAR). Remote sensing, they conclude, has played a large role in understanding APAR as previous field methods were locally specific and heavily problematic to model from. Ruimy et al.

(1999) examined APAR and plant's light-use efficiency in multiple models concluding that variations in light-use efficiency will cause intra-model variations while APAR is the root cause for most spatial variations.

Schloss et al. (1999) pay particular attention to sensitivity for precipitation and temperature. Their findings show the greatest variations of NPP in environments limited by either precipitation or temperature. Churkina et al. (1999) found similar results for moisture in general. Kicklighter et al. (1999) as well as Milne and Cohen (1999) focus on model variations between biomes, while a number of studies also focused on coordinating modeling efforts (Olson et al. 1999; Running et al. 1999; Thomlinson, Bolstad, and Cohen 1999) and field-based validation (Cohen and Justice 1999; Milne and Cohen 1999; Reich, Turner, and Bolstad 1999).

Remote Sensing

The major contribution of remote sensing to studying primary productivity has been its ability to measure fAPAR both spatially and temporally. Previous studies relied on a few field samples, which because of costs were inappropriate and misleading for regional to global NPP studies (Gower, Kucharik, and Norman 1999). Remote sensing allows for a more complete understanding of the variables used in NPP.

Normalized difference vegetation index (NDVI), a remote sensing product, has shown notable promise as a rough surrogate for NPP (Box, Holben, and Kalb 1989; Kobayashi, Matsunaga, and Hoyano 2005; Schloss et al. 1999). NDVI is simply a greenness index created as a ratio between red and near-inferred satellite bands. It is therefore readily available from many satellite platforms. Schloss et al. (1999:27) have demonstrated a strong correlation between NDVI and fAPAR. This relationship allows NDVI to be used in place of fAPAR when and where it is not available. Furthermore Los et al. (2000) developed a method to calculate fAPAR from NDVI based on their linear relationship. Although NDVI can be derived from most any satellite, NOAA's Advanced Very High Resolution Radiometer (AVHRR) is often used for NPP studies due to its large spatial extent and high temporal frequency (Box, Holben, and Kalb 1989; Goward, Tucker, and Dye 1985; Prince and Goward 1995).

The Moderate Resolution Imaging Spectroradiometer, or MODIS, was the first satellite sensor to directly measure fAPAR and therefore provides an improved means of calculating NPP (Running et al. 2004; Turner et al. 2006; Zhao et al. 2005). MODIS measurements of fAPAR are better than field measures, NDVI, or other satellite products because it offers continuous spatial coverage as well as increased temporal frequency which can be directly applied to measuring NPP (Cohen and Justice 1999; Running et al. 1999; Zhao, Running, and Nemani 2006). Not only this, but it has been specifically designed for this application rather than a multitude of applications (Running et al. 1999).

Remote sensing techniques use fAPAR coupled with a vegetation light-use efficiency (ε) to model NPP (Gower, Kucharik, and Norman 1999:38). The ε determines how well specific plants fix solar radiation into carbon (Bradford, Hicke, and Lauenroth 2005; Lobell et al. 2002; Ruimy et al. 1999). ε is usually based on a look-up table of published values for general biomes but can also be derived for regionally-specific land-cover classes. These values are subject to both short-term and long-term changes and must be continually re-evaluated (Cohen et al. 2006; Heinsch et al. 2003; Yang et al. 2006; Zhao et al. 2006).

MODIS-derived NPP uses a regionally-specific, land-cover classification algorithm to define each biome in a remotely-sensed scene (Bradford, Hicke, and Lauenroth 2005). Then eddy-covariance flux towers, measuring a multitude of biogeochemical exchanges and permanently stationed in representative land-cover classes, compute the biome specific ε values (Turner et al. 2006). In effect remote sensing techniques correct generic biome estimates by calculating ε for every pixel (Ruimy et al. 1999).

Running et al. (1999) demonstrate the value of using field measurements in conjunction with remotely-sensed data. Long established field stations, monitoring biogeochemical fluxes, are now being integrated directly with the automated computation of NPP. There are field stations producing data to parameterize the equations (Running et al. 1999; Turner et al. 2006) as well as stations collecting data for validation (Cohen and Justice 1999; Reich, Turner, and Bolstad 1999). Kang et al. (2002) demonstrate how integrating the separate parts: fAPAR, land-cover classification and ε, can develop much more detailed estimates of NPP.

When these techniques are all applied to a long time series, NPP dynamics become apparent (Hicke et al. 2002). In their study of North American NPP from 1982-1998, Hicke et al. (2002) show regional increases and decreases in NPP based on seasonality. Some climatic variables dominate in certain environments while other variables dominate in others (i.e. temperature controls NPP in western Canada and Alaska, while moisture dominates NPP in Texas (Hicke et al. 2002:13)).

Agricultural Census

By using U.S. agricultural census data scientists have been able to explicitly explore NPP in agricultural regions of the U.S. The agricultural census, administered and maintained by the USDA, has been shown to be a robustly constructed, although not without faults, database offering a vast wealth of economic data relating to the production of agriculture as well as the industry as a whole. Compiled from both short- and long-form surveys and field enumerations (Prince et al. 2001:1195-1196), the census is both comprehensive and as complete as logistically possible (USDA 2004a). Not only is the census robust but it offers well over 160 years of historical perspective. The agricultural census is therefore a one-of-a-kind resource for researchers seeking uniform, national coverage with great spatial detail and long historical record (USDA 2004a).

To measure NPP, data is either used in its raw, reported form (i.e. area and yield) (Specht, Hume, and Kumudini 1999) or it is converted from economic yield to NPP (Bradford, Hicke, and Lauenroth 2005; Hicke, Lobell, and Asner 2004; Lobell et al. 2002; Prince et al. 2001). This data is then used with a variety of techniques to analyze for trends across space and/or time. An historical perspective (Hicke, Lobell, and Asner 2004; Turner 1987) is able to show how changing management practices have either improved or worsened carbon sequestration and can provide important lessons for future management. Comparing natural systems to cultivated systems (Bradford, Hicke, and Lauenroth 2005; Lauenroth, Burke, and Paruelo 2000) shows the potential for people to both provide food and sequester greater amounts of carbon when environmental conditions are appropriate. Methods have also shown the diversity of applications for the data, particularly as a means of validating other methods such as remote sensing models (Bradford, Hicke, and Lauenroth 2005; Izaurralde et al. 2006).

Although research using U.S. agricultural census data is well-developed, research as a whole still offers avenues for further refinement. First, although the census offers amazing insights for agriculture, it does not contain information on other plants (grasslands and forests for example) (Bradford, Lauenroth, and Burke 2005; Hicke et al. 2002; Hicke and Lobell 2004; Hicke, Lobell, and Asner 2004; Lobell et al. 2002; Prince et al. 2001). Alternative techniques are sometimes required to account for non-agricultural vegetation (Kroodsma and Field 2006; Turner 1987). Second, regionally-specific parameters required to convert data to NPP are hard to come by and therefore can introduce bias. As a result most studies use the same published parameters regardless of time or place (Hicke, Lobell, and Asner 2004; Kroodsma and Field 2006; Lauenroth, Burke, and Paruelo 2000; Lobell et al. 2002). Thirdly, validation of modeled results has, at best, been piecemeal. It has been dominated by self-referencing with only a few studies comparing census-derived results to alternative methods (Hicke et al. 2002; Lobell et al. 2002). These faults are more a product of the relative newness of this technique, and time will possibly self-correct these faults.

Harvest index is the most important variable used to convert the agricultural census to NPP. Harvest index (HI) is a ratio between the economically viable part of a plant and the remainder (Hay 1995:198). Agricultural literature has chronicled the changes in HI (Hay 1995; Martin, Leonard, and Stamp 1976; Sinclair 1998). This is important because one must use both spatially as well as historically correct values. Prince et al. (2001) recognized the spatial component but also discussed the general lack of regionally-specific values for many crops. For her study in Georgia, Turner (1987) was able to find historically accurate values. The historically accurate HI values allowed her to compare the evolution of harvest techniques to the changes in production of NPP.

Human Appropriation of Net Primary Productivity

Human appropriation of net primary productivity, HANPP, compares primary productivity to what humans either consume, replace, or otherwise manipulate (Vitousek et al. 1986:368). It is an energy balance between what is present (or would be present) and what humans appropriate. HANPP speaks to two groups of literature: human sustainability and biodiversity.

Sustainable HANPP tends to focus on how HANPP has changed throughout human development (Giampietro, Bukkens, and Pimentel 1992; Haberl 2006), and whether or not current rates are sustainable (Wackernagel et al. 2002). Giampietro et al. (1992) evaluated HANPP for three types of society: hunter-gatherer, agrarian, and industrialized. Although one could draw from Giampietro et al.'s Neo-Malthusian predictions, a bleak fate from unsustainable consumption, more importantly we see HANPP as a powerful modeler of energy consumed by humans.

An historical look at human appropriation like this offers two benefits. First a pattern of past consumption is illustrated. Second, this trajectory can be used to evaluate how sustainable current trends might be. Haberl (2006) provided such a prediction where, by the year 2050, human-controlled energy inputs will account for over 50% of NPP. Tilman et al. (2001) found similar results where agricultural demand will become so great the impact will lead to "unprecedented ecosystem simplification, loss of ecosystem services, and species extinctions." So HANPP not only impacts human sustainability but also that of everything else in the ecosystem, the second dialog of HANPP studies.

Many studies link human appropriation to decreasing biodiversity (Haberl, Fischer-Kowalski et al. 2004; Wright 1990; Williams et al. 2005; Vitousek et al. 1997). It is expected that increases in NPP support greater species diversity. Unfortunately, according to Wright (1990), humans have conservatively disrupted natural energy flows by up to 30%, co-opting that energy for our sole use. As a result species diversity will decrease as the remaining energy decreases. Haberl et al. (2004) tested this theory for a number of plots in eastern Austria and found results supporting Wright's species-energy hypothesis.

Global percentages of HANPP range between 10 and 55% of terrestrial NPP (Rojstaczer, Sterling, and Moore 2001:2549). Predictions vary mainly due to the inputs used and their quality. Vitousek et al. (1986) calculated it as 40%. Refinement of major biomes resulted in estimates of appropriation between 20 and 30% (Wright 1990:189); and by modeling HANPP spatially, Imhoff et al. (2004) estimated 31% was appropriated. The remainder of this chapter looks at these studies in greater depth.

Aspatial Studies

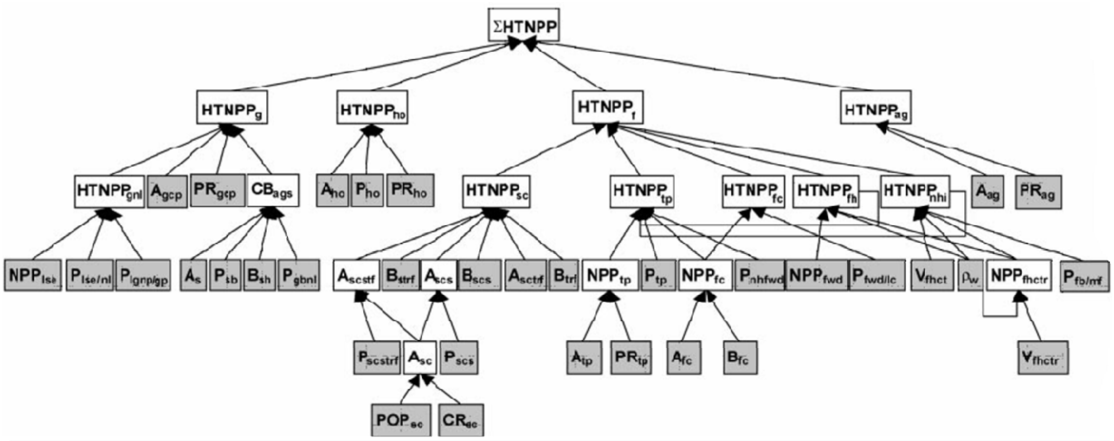
Vitousek et al. (1986) were the first to publish on HANPP. They estimated human appropriation upwards of 40% of global carbon stocks. Many authors have critiqued Vitousek et al.'s work centering on their rudimentary methods. Estimates of biome size, vegetation efficiency factors, and land-cover conversions are critiqued as being too simplistic or non-existent (Dukes 2003; Field 2001; Krausmann 2001; Rojstaczer, Sterling, and Moore 2001). Regardless, Vitousek et al. (1986) remain the benchmark that all subsequent work draws from, either through methodology (Haberl 1997; Prasad and Badarinth 2004; Rojstaczer, Sterling, and Moore 2001), or for comparison (Field 2001; Imhoff et al. 2004; Prasad and Badarinth 2004).

Vitousek et al. (1986:368) divided human appropriations into three broad categories, or estimations: low, intermediate, and high. The low estimate included consumption of plants for food, fuel, timber. Intermediate estimates included altering the land-cover to increase productivity through intensive management and husbandry. High estimates took into consideration conversion from one land-cover to another, such as forest to urban, where biomass production is severely reduced if not totally replaced. They then used published averages and or expert opinion to calculate how many petagrams (Pg) of carbon each activity consumed. Vitousek et al. (1986) concluded humans appropriate roughly 40% of global NPP.

While Vitousek's study goes a long way to establish the methodological framework for future studies it has been recognized for ignoring or misjudging the impact of certain activities. Most notably is how Vitousek et al. incorporated agricultural NPP. They viewed agriculture as purely extractive where all biomass is harvested. This flaw was quickly noticed and remedied in other studies, and as the result we see the emergence of refined methods uniquely devoted to agricultural NPP (Bradford, Lauenroth, and Burke 2005; Hicke, Lobell, and Asner 2004; Lobell et al. 2002; Prince et al. 2001). Another issue misinterpreted was the impact of grazing on pastureland. Here Vitousek et al. fail to acknowledge the positive and needed influence of large herbivores to a rangeland system. Finally Vitousek et al. as well as others (Field 2001; Haberl 1997; Imhoff et al. 2004; Wright 1990) rarely acknowledge human activities increasing NPP such as in reforestation.

HANPP is singularly about human appropriation, but in understanding human sustainability understanding all facets of NPP use/ manipulation is required. Prasad and Badarinth (2004) drew on Vitousek et al.'s techniques, as well as others (Prince et al. 2001; Rojstaczer, Sterling, and Moore 2001), to understand HANPP in India with surprising results. Even though there was a slight increase in HANPP between 1961 and 1998 it was dramatically offset by increases in NPP from aforestation and agriculture (Prasad and Badarinth 2004:58). The expansion of forest and agriculture increased regional NPP thereby decreasing HANPP.

Rojstaczer et al. (2001) have greatly expanded on Vitousek et al.'s (1986) methodology. Their study is the most robust of aspatial HANPP studies. Figure 2 illustrates the hierarchy of HANPP (they use the term HTNPP; human appropriation of terrestrial net primary productivity). Furthermore they focus on the uncertainty of data sources and calculations.



Source variable	Description	Prior estimate (1)	Contemporary mean	SD mean	Number of samples
A_{ag} (m^2)	Area of agricultural land (21, 33–43)	1.6×10^{12}	1.3×10^{12}	0.33	11
A_{fc} (m^2)	Area permanently cleared for population increase and colonization (26, 43–48)	1.2×10^{11}	1.3×10^{11}	0.23	7
A_{gcp} (m^2)	Area of forest converted to grazing for all time (21)	7×10^{12}	3.3×10^{12}	0.50	1
A_{ho} (m^2)	Area of human-occupied lands (38–40, 49)	2×10^{12}	1.8×10^{12}	1.2	4
A_s (m^2)	Area of savanna (39–40, 42, 44, 50–52, 215)	1.5×10^{13}	1.7×10^{13}	0.46	8
A_{sctrf} (m^2/year)	Area cleared in tropical virgin forests by shifting cultivation (1, 53, 54)	1.0×10^{10}	3.8×10^{10}	0.79	3
A_{tp} (m^2)	Area of tree plantations (12, 22–24, 47, 55–57)	1.5×10^{12}	1.2×10^{12}	0.18	6
B_{fc} (Pg/m^2)	Biomass of forest areas permanently cleared for population increase and colonization (1, 11–14, 27, 47, 48, 50, 58–109, 111–116, 214)	2.2×10^{13}	3.3×10^{13}	0.91	61
B_{scs} (Pg/m^2)	Biomass of savanna in shifting cultivation (including below-ground) (13, 39, 48–50, 54, 98, 109, 110, 113–129)	8.5×10^{12}	5.6×10^{12}	1.1	23
B_{sh} (Pg/m^2)	Biomass of above-ground grasses in burned savanna (1, 103, 104, 109, 130–141)	3.9×10^{11}	6.7×10^{11}	0.60	14
B_{strf} (Pg/m^2)	Biomass of secondary tropical forest (including below-ground) (11, 12, 48, 72–89, 109, 115, 116, 142, 143)	1.8×10^{13}	1.7×10^{13}	0.65	20
B_{trf} (Pg/m^2)	Biomass of tropical forests (including below-ground) (11, 13, 16, 27, 47, 48, 50, 84–103, 107–114, 143–150)	3.9×10^{13}	3.6×10^{13}	0.58	43
CR_{sc} (m^2 $person^{-1}$ $year^{-1}$)	Clearing rate of shifting cultivation (1, 53, 102, 151, 152)	2.0×10^3	1.7×10^3	0.16	5
NPP_{fwd} (Pg/year)	NPP of firewood (27, 44, 54, 55, 152–159)	1.0	0.90	0.80	10
NPP_{lse} (Pg/year)	NPP eaten by livestock (1, 8, 109, 160–164)	2.2	3.6	0.53	5
$P_{fb/mf}$	Proportion of forest biomass relative to merchantable fraction (1, 15, 16, 68–72, 89, 90, 104, 107, 115, 158, 166–171)	2.1	2.7	1.2	21
$P_{fwd/lc}$	Proportion of firewood that is met by land clearing and cultivation (102, 104)	0.30	0.65	0.75	2
P_{gbnl}	Proportion of burning on natural grazing lands (1)	0.43	0.43	0.50	1
P_{ho}	Proportion of productive human-occupied lands (13)	0.40	0.40	0.50	1
$P_{lgnp/gp}$	Proportion of natural pasture grazed by livestock relative to all grazed pasture lands (1)	0.50	0.50	0.50	1
$P_{lse/nl}$	Proportion of NPP eaten by livestock that comes from natural lands (172)	0.68	0.87	0.50	1
P_{nhfwd}	Proportion of firewood harvested but not used every year (1)	0.50	0.50	0.50	1
POP_{sc}	Population that uses shifting agriculture (25, 173)	2.0×10^8	4.5×10^8	0.15	2
PR_{ag} (Pg m^{-2} $year^{-1}$)	Productivity of agricultural lands (1, 13, 14, 30, 31, 39, 42, 48, 91, 98, 105, 109–112, 116, 129, 174–178)	9.4×10^{13}	9.0×10^{13}	0.55	16
PR_{gcp} (Pg m^{-2} $year^{-1}$)	Productivity of lands converted to pasture (1, 13, 14, 30, 31, 39, 48, 50, 101, 105, 109–112, 116, 129–132, 154, 178–196)	1.4×10^{12}	1.1×10^{12}	0.82	37
PR_{ho} (Pg m^{-2} $year^{-1}$)	Productivity of human-occupied lands (39, 197)	5.0×10^{13}	3.5×10^{13}	0.60	2
PR_{tp} (Pg m^{-2} $year^{-1}$)	Productivity of tree plantations (12, 13, 39, 55, 95, 96, 109, 198)	1.75×10^{12}	1.60×10^{12}	0.81	8
P_{sb}	Proportion of savanna burned annually (44, 54, 125, 157, 179, 199–202)	0.40	0.40	0.75	9
P_{scs}	Proportion of shifting cultivation in savannas (1, 72, 152, 203, 204)	0.43	0.46	0.41	5
P_{scstrf}	Proportion of shifting cultivation in secondary tropical forest (44, 53, 72, 87, 109, 152, 204)	0.57	0.64	0.42	6
P_{tp}	Proportion of wood that humans use of tree plantation origin (22, 55)	0.25	0.22	0.50	1
ρ_w (Pg/m^3)	Density of fiber/construction wood (1, 12, 15, 16, 89, 99, 106, 107, 115, 170, 205–213)	6.0×10^{-10}	5.6×10^{-10}	0.55	17
V_{fhct} (m^3/year)	Volume of forest harvest for wood used for construction and fiber in temperate areas (26, 27, 36)	1.65×10^9	1.1×10^9	0.1	52
V_{fhctr} (m^3/year)	Volume of forest harvest for wood used for construction and fiber in tropical areas (27)	4.0×10^8	3.9×10^8	0.50	1

Figure 2: Template used to estimate HTNPP. The formula on which the template is based is the intermediate calculation of Vitousek et al. (1986). Gray boxes represent independent parameters.... White boxes represent dependent parameters and are intermediate or final calculations (2001).

Rojstaczer et al. (2001) focused on primary-source data from the literature to avoid bias. They increased their confidence in the data by calculating averages across multiple data sources, thereby decreasing errors inherent in an individual one. The application of MonetCarlo techniques allowed them to highlight a very important point which other studies fail to discuss at great length. Because the technique incorporates known and unknown errors their estimate for HANPP ranges from 10 to 55% (Rojstaczer, Sterling, and Moore 2001:2550). This range represents great uncertainty in the model parameters. Chief among these were agricultural productivity and biomass of secondary tropical forests (Rojstaczer, Sterling, and Moore 2001). A better understanding of the mechanisms and measurements for each parameter was required to increase overall confidence for this global aspatial study.

These aspatial HANPP studies (Prasad and Badarinth 2004; Rojstaczer, Sterling, and Moore 2001; Vitousek et al. 1986; Wright 1990) offer useful glimpses into human sustainability. However, they fail to acknowledge the spatial pattern of both NPP and HANPP brought about by natural and social factors (e.g. climate or industrialization). Methodological complexities and data availability have long hampered calculating HANPP spatially. Accounting for the flow of energy has also been a major hurdle for spatial HANPP studies (Dukes 2003) while examining the system, be it Earth (Rojstaczer, Sterling, and Moore 2001; Vitousek et al. 1986) or a nation (Prasad and Badarinth 2004). The study area as a single unit removes the need to model space explicitly and the accompanying complexities.

Spatial Studies

What the aspatial models lack are spatial relationships. They are all based on single values to represent each parameter of the HANPP model across all space. Although Rojstaczer et al. (2001) collect data from satellite-derived sources and country-by-country reporting (resolution) they fail to spatially examine the data for any pattern. These studies are spatially independent with no sense as to where human appropriation is greatest, most rapid, or most degrading to ecosystems; all important unknowns when assessing the sustainability of human activity. Unique among HANPP studies are Imhoff et al. (2004) and Haberl et al. (2007) because they do take spatially-explicit approaches to modeling HANPP.

The Imhoff et al. produce one map showing HANPP (Figure 3a), and a second showing the 'balance' between HANPP and produced NPP (Figure 3b) (Imhoff et al. 2004:871). What this shows are important spatial patterns of HANPP. To produce these maps Imhoff et al. took national statistics, provided by FAO, applied a number of multipliers to include belowground NPP and production efficiencies, and then calculated a per capita HANPP per country that they applied to a global grid. This grid matched the resolution of their NPP calculations and could be used to illuminate patterns of NPP consumption (see Figure 3b).

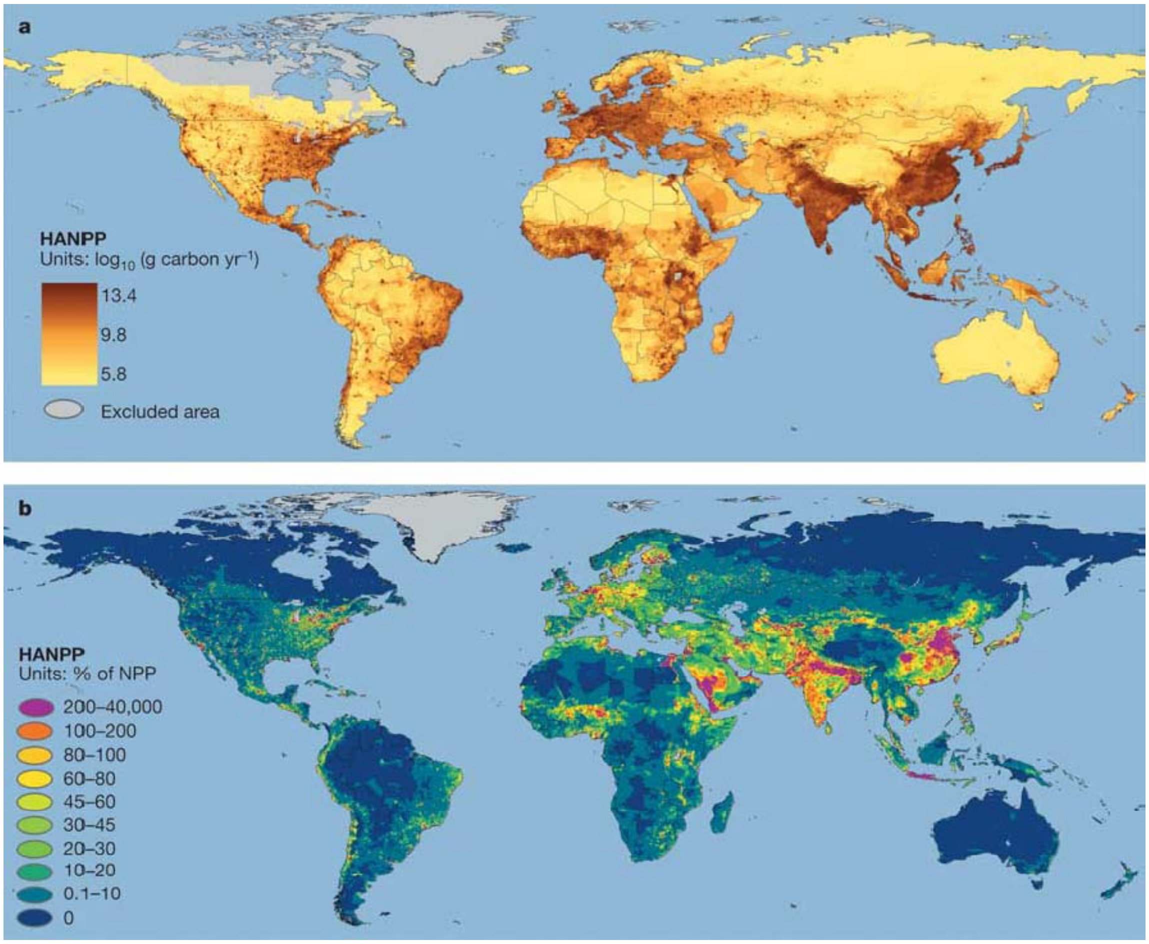


Figure 3: Spatial distribution of HANPP from Imhoff et al. (2004).

While this study represents a new step for HANPP there are some significant drawbacks in its methodology. First, is that per capita HANPP is assumed homogenous for each nation. The authors are aware of this (Imhoff et al. 2004:871), as other studies (Haberl et al. 2002) have pointed out the intra-national variability of HANPP. Secondly, their parameters to measure HANPP, which focus solely on terrestrial NPP, neglect various other forms such as appropriation from aquatic systems (Field et al. 1998) and ancient systems (fossil fuels) (Dukes 2003). Finally their measure of HANPP is based on the

NPP required to produce consumed goods leaving out the loss of NPP through land-cover transformations (Imhoff et al. 2004:872).

In 2007, Haberl et al. published the second extensive spatial HANPP study at the global scale (Haberl et al. 2007). This study follows much of the methodology set forth by Imhoff et al. Methods and particularly data sources are refined based on critics of the above study. Haberl et al. estimate that 23.8% of potential NPP was appropriated by humans globally in 2000 (Haberl et al. 2007)

Austrian Comparisons

At a national scale the work of Harberl et al. (1997; 2001; 2004; 2004) and Krausmann (2001, 2004; 2002) in Austria offer the greatest detail for reviewing HANPP. This research chronicles the evolution of HANPP methods drawing on the rich data archives of that country. There is a clear development of methodology and data between the earliest 1997 study and the latest. Early studies mirrored Vitousek et al.'s (1986) work closely, but subsequent studies helped refine classification schemes and efficiency factors. They relied on Austrian agricultural and forestry statistics and were able to calculate the total amount of biomass removed for crops, livestock and forestry. Although their research began by mirroring Vitousek et al. (1986) closely (Haberl 1997) they expanded their research to explore temporal patterns in HANPP (Krausmann 2001) as well as rudimentary spatial patterns (Haberl et al. 2001).

Haberl's first study in 1997 was very much in line with Vitousek et al.'s (1986) seminal work. The study was novel in that it applied Vitousek et al.'s methods to a finer spatial scale (Austria), and drew from a much more refined and robust data archive (Haberl 1997:143). Haberl found Austria to appropriate greater quantities of NPP than Vitousek et al.'s global value (41% for Austria compared to 39% as Vitousek's high global estimate) (Haberl 1997:144). The discrepancy was easily explained since Austria is more developed than the global average and therefore appropriates more. Regardless Haberl's (1997) results compared well within Vitousek et al.'s (1986) and the two studies helped support one another's estimates. Haberl's 1997 attempt still suffered from the same aspatial issues: removing any spatial patterns, and relied on similar methodologies as Vitousek et al. (1986).

Krausmann (2001), a colleague of Haberl, advanced the Austrian HANPP research one step further by introducing a temporal dimension. The statistic of 40% appropriation of NPP set Krausmann to investigate the temporal transformation of HANPP (Krausmann 2001:18). Following the same process as Haberl (1997), he calculated HANPP for each decade between 1830 and 1995. Results showed a strong temporal trend influenced by modernization. Industrialization and market demand led to intensification and greater appropriation of some resources (paper and pulp), while technology led to intensification and concentration of agriculture (Krausmann 2001:23-24). The net result was decreased agricultural space and increased woodlots with an overall decrease in HANPP (Krausmann 2001:23). These important findings show that first, HANPP is not static or necessarily increasing, and second, social demands coupled with advancing technology are strong determinants of HANPP.

Haberl working with Krausmann and others (2001) reapplied their techniques to the Austrian statistical data but this time with a spatially-explicit component. The use of remote sensing, which allowed spatial classification of land-cover types, was used in conjunction with agricultural statistics. The results from using the more refined, spatially-explicit data increased HANPP to around 50% (Haberl et al. 2001:935). The use of regions allowed patterns of HANPP in Austria to emerge. The work though novel, failed to provide enough detail as some data (e.g. satellite-derived land-cover) was fairly well defined spatially while other data was still based on regional (e.g. crop yields) or national (e.g. non-agricultural productive) averages (Haberl et al. 2001:933). As a result of this scale mismatch variations in HANPP between land-cover types are misleading.

Imhoff et al. (2004) used similar methods as Haberl et al. (2001) except they took a larger, global view of HANPP using a grid system. Different methodological issues present themselves when comparing these two studies: the global and the national. Efficiency factors for vegetation change dramatically depending on place, harvest techniques, timing, and the classification of biomes. As scale becomes more refined this leads to the requirement of more detailed data sources as well as more refined methods. These complications have prohibited many from attempting such studies. Haberl et al.'s

(2001) work demonstrates these frustrations. The differences between data sources and the aggregation required to reach a common unit of measure (NPP) resulted in different estimates of HANPP, up to four mega tons of carbon a year in some categories, and different levels of confidence between land-cover classes (Haberl et al. 2001:934).

Local Case Studies

There have been other studies seeking to understand specific aspects on HANPP. These studies narrowly focus on specific environments and/or unique avenues of human appropriation. Local studies of HANPP also do not attempt to explain all the flows of energy within the system. This would be quite cumbersome unless the society was self-contained. At the local level too much appropriated NPP is imported for there to be any real insights into local patterns. Instead the local level affords researchers an in-depth look at the flow of energy from specific resources and refinement of techniques to measure it.

As an example, Robbins and Birkenholtz (2003) looked specifically at the expansion of turf grass in the American lawn. At a city scale (Columbus, Ohio) they were able to evaluate the impacts of high-intensity monoculture lawns. By determining the extent and growth rates they could also estimate the demands lawns have on other resources: water usage, fertilizers, and insecticides (Robbins and Birkenholtz 2003:190). At regional to global scales there is little done to incorporate these highly productive, carbon sequestering, fragments of land. They are simply lost due to scale.

Krausmann (2004) was afforded similar insights from four villages in Austria. By looking at detailed studies of LUCC he was able to "interconnect individual biophysical processes and aspects and to view the transformation of agriculture as a complex process" (Krausmann 2004:768). Not only are data more refined and detailed at this scale but also quality can be controlled much more thoroughly. At the village level Krausmann could link decision making directly to land-use changes and decipher the impact each decision had.

Furthermore, detailed case studies afford a more robust understanding of environmental conditions. Take for instance Cardoch et al.'s (2002) work on HANPP in the Ebro and Mississippi deltas. By studying the biological cycles of each, coupled with human appropriation, they concluded that not only do human uses change in response to social and environmental change but so do biological ones. Human appropriation not only lowered NPP through harvesting and land-cover change, but anthropomorphic changes altered multiple delta system dynamics, which further reduce natural production (Cardoch, Day, and Ibanez 2002:1051).

Finally it is important to keep in mind that HANPP is only a measure of what humans appropriate from their environment. It is not a measure of how much people are physically consuming. Haberl explored the relationship between what humans appropriate and what they consume and has drawn clear distinctions between the two

(Haberl 2001a, 2001b). Haberl (2001b) defines the dichotomy as human appropriation on one side and socioeconomic energetic metabolism on the other. HANPP represents a change in productivity due to land conversion and/or through harvesting (Haberl 2006:95), while the energetic metabolism of societies: "analyzes physical exchange processes (material and energy flows) between human societies…." (Haberl 2001b:12).

Through social metabolism Haberl (2001a, 2001b) explored how globalization and particularly fossil fuels have allowed societies to be area-independent for their energy resources. Social metabolism might be high in a large city but the majority of the appropriated material/energy may be coming from all over the world. Therefore to understand human sustainability, one must recognize that the overwhelming majority of our energy comes from ancient NPP – fossil fuel (Dukes 2003). If HANPP is to achieve its goal of measuring the harvest of energy from the natural system, accounting for fossil fuel is key. Dukes attempted to deal with this but conceded that his methods were not robust enough to properly measure the HANPP of fossil fuel (Dukes 2003:39). Although there are attempts to measure the energy requirements of societies (Haberl 2001b, 2006) they tend to be about the flow of energy between society (socioeconomic energetic metabolism) rather than human appropriation, leaving Dukes (2003) the sole attempt.

CHAPTER III

METHODS

This study further develops HANPP methods by examining the affects of agricultural and timber industries in their harvest of net primary productivity. As previously seen HANPP studies have sought to differentiate and quantify the amount of NPP appropriate by humans through different means (Haberl 1997; Imhoff et al. 2004; Rojstaczer, Sterling, and Moore 2001; Vitousek et al. 1986). Informed by such studies, this thesis quantifies the amount of NPP harvested within Texas, per county, for a large number of agricultural activities. First a base layer is established to represent the current state of NPP in Texas. This is accomplished through the modification of a remotely-sensed MODIS (NASA's Moderate Resolution Imaging Spectroradiometer) product. Second, datasets are acquired and processed for every major agricultural and timber industry in Texas (given data exists). This data is then spatially distributed by county; the smallest reporting unit from available resources. Next all agricultural data are converted from economic yields to harvested NPP using a formula introduced by Prince et al. (2001) and rigorously tested in agriculturally intensive areas of the U.S. (Hicke and Lobell 2004; Lobell et al. 2002). Modifications were needed to cope with different types of crops, reported units, and timber statistics. Results from these methods are used to compare harvested NPP to actual NPP derived from the MODIS product.

This chapter begins with a description of the framework introduced in Prince et al.'s model (2001). It is followed by how this study modifies and implements it. The limitations and assumptions inherent in the model are explored followed by a development of the data. This will chronicle the development and processing of each data source along with discussions of associated variables used to implement them.

Model

The model used here is adapted from Prince et al. (2001). In their study the authors use total harvested crop yield data from the U.S. Department of Agriculture's National Agricultural Statistics Service (USDA NASS). Their method involves recalculating all the data into a common unit of measure. For HANPP studies, carbon is the standard unit and is expressed as g C m^{-2} yr^{-1}. To do so the data is converted from reported yield to mass, then to dry mass, and finally to carbon. The belowground portion of the crop is accounted for as well as plant parts lost during harvest. They apply this to nine major crops in the Midwestern U.S. by county for one point in time as well as a subset over fourteen years. The large spatial extent was used to examine the variability of their methods through space while the long time series showed temporal variability. When calibrated using area-specific conversion factors they found their methods to be highly successful.

Other studies have further refined Prince et al.'s methods (Hicke and Lobell 2004; Hicke, Lobell, and Asner 2004; Lobell et al. 2002). These studies expand on the spatial extent of Prince's work to cover the whole nation as well as situate its use within the carbon credit program to promote sustainability (Hicke and Lobell 2004). They also expound on some of the limitations of Prince's methods as discussed later.

The method uses two equations to convert total crop yield per county to NPP (g C m^{-2} yr^{-1}). The USDA NASS database provides two main statistics: total yield and harvested area for each crop type. Total yield is reported in economically relevant units such as bushels, pounds, or tons. A conversion factor is required to transform yield to weight (g). Another variable will then account for the moisture content of the harvested product resulting in dry mass. This is then converted to units of carbon. These steps only account for the economic part of the plant therefore a harvest index is used to account for the remainder of the harvested crop. Harvest indices were a strong economic measure used over a long period of time in agriculture, though their usefulness as such seems to have reached its end (Hay 1995). This index now finds use in ecological studies as well as sustainability studies such as this. The portion of belowground plant matter is not incorporated in the harvest index and must therefore be accounted for as the final piece in Prince's first equation. This variable represents the ratio of belowground plant to aboveground. The product of this equation is carbon production for the county (g C yr^{-1}). The second equation divides production by the area harvested yielding NPP (g C m^{-2} yr^{-1}). Area harvested, as reported by NASS, is in acres and therefore must be converted to square meters.

Combining the conversion factors and variables the equation is as follows:

$$P = \sum_i \frac{PC_i * MRY_i * (1 - MC_i) * C}{HI_i * fAG_i} \qquad \text{(4) Crop Production}$$

where P is production in units of carbon (g C yr^{-1}). i represents each harvest activity (i.e. each crop). PC_i is the total amount of crop produced in a county and is usually reported as a weight or volume (tons or bushel for example). This is the value recorded in the NASS dataset. MRY_i converts the reported crop production to units of mass (g). It is simply a multiplier. MC_i is the percent moisture of a harvested crop. Subtracting it from one (1) gives the multiplier to convert to dry mass. C is simply a constant value (0.45 g C g^{-1}) to convert dry plant mass to carbon. HI_i is the harvest index and accounts for that part of the plant lost in harvest. fAG_i is the aboveground fraction of the plant and is used to account for root mass. Taking this one step further P is divided by total area (A_i) in square meters of each crop to give NPP (g C m^{-2} yr^{-1}). The result is the amount of NPP harvested from each activity in every county.

$$NPP = \frac{P}{\sum_i A_i} \qquad \text{(5) NPP}$$

MRY, *MC*, *HI*, and *fAG* are all found both in the NPP literature (Hicke and Lobell 2004; Hicke, Lobell, and Asner 2004; Lobell et al. 2002; Prince et al. 2001) as well as agricultural literature (Donald and Hamblin 1976; Johnson, Allmaras, and Reicosky 2006; Martin, Leonard, and Stamp 1976). The concluding section of this chapter will look in more depth at the development of each of these variables for different crop type.

Fruit and vegetables are dealt with in a similar manner as above with one minor exception: data is reported only in acres harvested. Therefore those acres must be converted to total quantity produced (i.e. PC_i) by multiplying acres harvested by published yields (yield is quantity of product produced per acre). After calculating total production the methods continue as before.

Timber harvests are reported by the Texas Forest Service for 43 east Texas counties. These counties are the major timber-producing counties in Texas and within each timber is one of, if not the main industry (Xu 2006a). Texas Forest Service reports the total volume of pine and hardwoods harvested for each county. They also publish calculations on timber residues lost during logging and milling (Xu and Carraway 2005). Because residue represents the harvest index but is a volume rather than percentage equation (4) Crop Production, is modified slightly for timber harvest.

$$P = \sum_i \frac{(PC_i + LR_i) * MRY_i * (1 - MC_i) * C}{fAG_i} \qquad \text{(6) Timber Production}$$

P is still production (g C yr^{-1}), and i is each crop type (pine or hardwood). PC_i is timber volume harvested before milling (ft^3). LR_i is the logging residue also as a volume. LR_i replaces HI_i in equation (4) Crop Production. MRY_i converts from logged volume (ft^3) to units of mass (g). MC_i is still percent moisture, and again C converts to carbon. fAG_i

remains as the measure of root to shoot. The result is the amount of carbon extracted through logging. Finally dividing P by area (A_i) as in equation (5) NPP, yields harvested NPP (g C m^{-2} yr^{-1}) of timber.

The resulting datasets, one for each harvest activity, show total agricultural yield, area harvested, total production in carbon, and harvested NPP per county for the study period. The data is then joined to a spatially-explicit dataset of Texas counties. This is done within a GIS (Geographic Information System) environment. The result is spatially distributed data, capable of being displayed and analyzed in map form. This product is then comparable to the actual NPP from the MODIS product.

Assumptions and Limitations

Although the model is very efficient at converting agricultural production values to harvested NPP there are a number of assumptions and limitations one must consider. They fall into two categories. The first are limitations on what the model is capable of accounting for. The second are assumptions and limitations regarding the parameterization of equation variables.

CAPABILITY: Prince et al.'s (2001) model was developed for a very specific dataset - USDA NASS, as well as for the Midwestern U.S. because it is dominated by grain crops. This means that certain crops were considered when constructing the above equations and therefore may not be ideally suited to Texas, although it may be methodologically possible. The fruit trees - peaches and pecans - are two such examples. For these orchard crops assumptions have to be made to account for management practices for pruning and harvesting. Since HANPP has not been studied in the U.S. for the large range of crops in this Texas study, many parameters are based on data from studies whose primary objective has not been HANPP. Although the modeling parameters applied to these crops are approximately correct (based on agricultural statistics and literature) validation in HANPP research has been all but non-existent. The most relevant study was that of Lobell et al. (2004), where results using methods similar to Prince et al. (2001) were compared to alternative modeling techniques. The differences in scale and crop types make assessing individual parameters impossible though. Prince et al. (2001:1199) acknowledge that woodland production cannot be measured by their equations and therefore they use a general estimation of woodland NPP. However, because a timber database exists for Texas, their methods and equations were adapted for woodland production in this study. Prince et al. (2001) also note that production on grazing areas is exceedingly difficult to measure. The ratio of above to belowground plant matter is strongly affected by grazing but the exact relationship is not fully understood. Measuring appropriation through livestock, they conclude, is exceptionally challenging and not yet practical for regional studies.

The application of these methods is also limited by data availability. Obviously one cannot convert yield to NPP if the yield is unknown. Hicke et al. (2004:5-7) discuss some of the limitations of the USDA NASS dataset; and their comments apply to all datasets. As will be discussed in greater depth (see Chapter III, Data), USDA NASS data is collected through various avenues, and not all crops are represented in the same degree. Reporting methods for a particular crop may change from year to year, and for some years data may not be reported at all. Further compounding data issues are the meaning of zero. Is it actually zero, were no data reported, or were reported data withheld for various reasons? In such cases the methods are limited by data quality.

Finally the methods adopted do not account for economic or environmental changes over time. As mentioned in the introduction, external forces may actually be controlling harvested NPP to a much greater extent than potential NPP. It is well known that precipitation and temperature control the potential of NPP (Churkina, Running, and Schloss 1999; Kicklighter et al. 1999; Turner et al. 2006). But Prince et al., in the time series part of their investigation argue that changes in management strategies, driven by multiple forces, can actually supersede the limiting effects of climate (2001:1200). One must also be aware that the application of these methods assume climate and management practices are uniform across space and time, even though this is obviously not the case. Regional adjustments could be made to account for such variability but finding appropriate local parameters is difficult. Therefore it is important to build a model with area specific variables when at all possible.

PARAMETERS: The construction and parameterization of the model has its own set of assumptions and limitations. The variables used in the NPP equations are both spatially and technologically dependant. If these are neither spatially or temporally relevant results can be greatly biased. Precipitation and temperature limit plant growth (Ruimy, Saugier, and Dedieu 1994) and, therefore, potential carbon sequestered. The lack of widespread cultivation in west Texas is evidence of this. Management and cultivation practices, centering in this case around irrigation from the Ogallala aquifer, can have an even stronger influence on potential carbon sequestered (Prince et al. 2001). The vast crop monocultures in the Panhandle are evidence of this. Therefore it is important that the variables used to model harvested NPP be appropriate to both the physical area and the management practices that are prevalent. This is clearly demonstrated by Imhoff et al. (2004) with the methods they use for global modeling of HANPP. As technology advances harvesting efficiencies increase, for example the harvesting practice of sugarcane has developed to optimize the number of harvests from a single plant before new planting take place. Furthermore they acknowledge that their parameters for global HANPP would grossly distort HANPP if used at smaller scales (Imhoff et al. 2004:872).

Belowground biomass is easily the least understood variable in the conversion equation (Jackson, Mooney, and Schulze 1997). The main reasons for this are lack of development in measurement methods and that the growth and turnover of root mass has been poorly studied: both of these stem from an underlying lack of interest (Gill et al. 2002). This is obvious when examining how belowground biomass is applied using

Prince's method. An acceptable generic value for *fAG* of 0.8 is routinely used, and known values are limited to only the most common crops (Prince et al. 2001:1198). It is important to bear in mind that the *fAG* 'rule of thumb' inherently assumes the belowground portion is always replaced after each harvest. This is not always the case. Perhaps the most notable example being sugarcane, where the root mass is left to regenerate new cane (Pinto, Bernardes, and Pereira 2006). In this way one root mass may be used for up to ten harvests before diminished returns necessitate a fresh planting (Martin, Leonard, and Stamp 1976:424).

Harvest indices have been shown by Johnson et al. (2006) and Prince et al. (2001) to vary due to climatic factors and management practices. Prince's study reveals that *HI* is relatively stable within ecologically similar regions (± 10%) but speculate on regional differences. They conclude by stating that regional differences in *HI* may be necessary to accurately calculate harvested NPP across regions. One conclusion from this research would be that choosing an appropriate harvest index is extremely important as it is spatially specific.

Data

The remaining section focuses on the specific datasets and the implementation of the above model. It is divided into two sections, the first dealing with satellite data, and the second with agricultural statistics. Methodological considerations are explained for each dataset. Furthermore the specific variables used for each timber and agricultural crop used in this research (Table 1) are justified.

Table 1: All timber and crop types used in this study.

Timber	Hardwood	Hay & Silage	Corn (Silage)
	Pine		Bahia Grass Seed
	Christmas Trees		Hay, All
	Woody Crop		Haylage, All
Grain	Corn (Grain)		Other Seed
	Oat		Rye Grass Seed
	Rice		Sorghum Silage
	Sorghum	Vegetables	Cabbage
	Wheat		Cantaloupe
	Proso Millet		Carrot
	Rye		Chili pepper
Other Field Crops	Cotton		Cucumber
	Peanut		Dry Onion
	Soybean		Pumpkin
	Sugarcane		Spinach
	Sunflower		Snap Beans
	Beans		Sweet Corn
	Cow Pea		Tomato
	Guar		Watermelon
	Pea	Fruit	Citrus
	Potato		Grape
	Sweet Potato		Peaches
			Pecan

Satellite

The first phase in the research was to produce a base layer capable of showing actual NPP across the state. Actual NPP is the amount of NPP produced in units of carbon per area. Actual NPP is important when measuring HANPP because it inherently accounts for human appropriation in the form of LUCC. Land-cover can be either modified or altered for human uses (Lepers et al. 2005) and can either increase or decrease NPP.

MOD17 – a Moderate Resolution Imaging Spectroradiometer (MODIS) product - calculates actual NPP over the Earth's surface. Because it computes actual surface level NPP the effects of LUCC are inherent within it. MOD17 is not a satellite image, but is a derived product that incorporates different MODIS imagery as well as ancillary data (most notably meteorological data) (Heinsch et al. 2003). Conceptually NPP has been shown as the difference between gross primary productivity (GPP) and autotrophic respiration (R_A) (Gower, Kucharik, and Norman 1999:38).

$$NPP = GPP - R_A \qquad \text{(7) Conceptual NPP}$$

In practice though this model is difficult to parameterize and therefore the equation is rewritten for remote sensing. In the rewritten form NPP is defined as a function of the fraction of absorbed photosynthetically-active radiation (fAPAR) and a light-use efficiency (ε) for different plant species (Field et al. 1998):

$$NPP = fAPAR * \varepsilon \qquad \text{(8) Functional NPP}$$

Both fAPAR and ε can be derived from satellite data making this equation optimal for spatial modeling of NPP. Although models come in a variety of forms (Schloss et al. 1999; Zheng, Prince, and Wright 2003) MODIS has algorithms to calculate fAPAR as well as field stations to refine ε (Gower, Kucharik, and Norman 1999; Ruimy et al. 1999; Turner et al. 2006). The User Guide to the MODIS NPP product further describes the

MOD17 algorithm and graphically illustrates the process (Figure 4) (Heinsch et al. 2003:10).

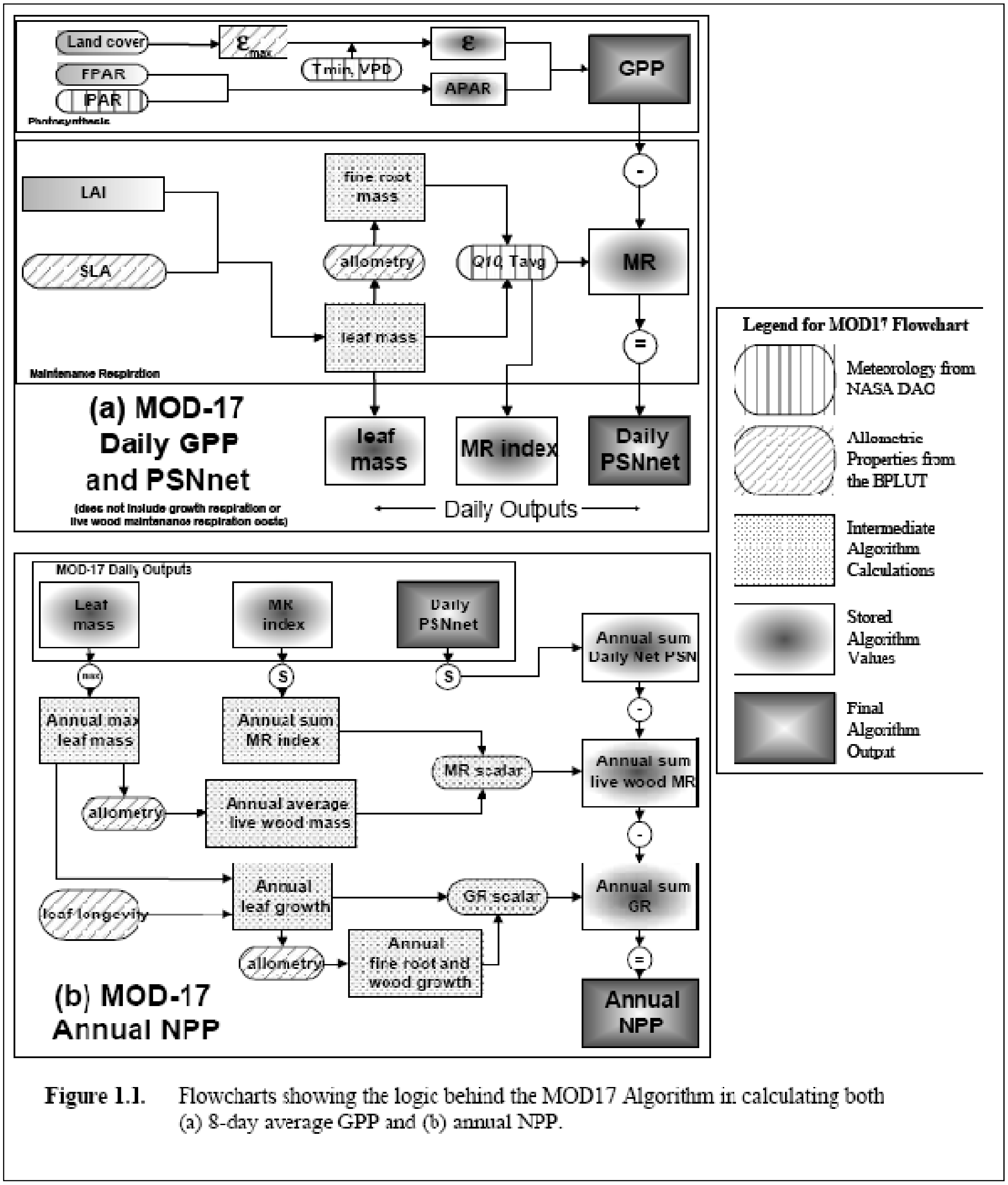


Figure 1.1. Flowcharts showing the logic behind the MOD17 Algorithm in calculating both (a) 8-day average GPP and (b) annual NPP.

Figure 4: MOD17 flowchart from Heinsch et al. (2003).

In short the MOD17 algorithm first calculates fAPAR based on PAR (all photosynthetically-active radiation) and meteorological data on a daily basis. The same meteorological data is used in combination with a look-up table of biome specific light-use efficiencies to calculate the best estimate of ε for the given daily conditions. These two variables (fAPAR and ε) are then used to calculate GPP. The inputs are next averaged over an eight-day cycle to account for anomalies such as cloud cover. The three inputs for NPP are derived from GPP and another MODIS product: Leaf Area Index (LAI). They are leaf mass and two plant maintenance respiration values (MR index and daily PSNnet). The MR index is an average respiration term, while PSNnet is the GPP remaining after subtracting both leaf and root maintenance respiration. The final NPP product subtracts respiration losses from primary productivity in accordance with the conceptual model of NPP, equation (7).

There are a number of projects running at field stations across the globe and within different biomes to help develop these algorithms (Cohen and Justice 1999; Running et al. 1999; Turner et al. 2006). MODLAND is charged with developing the MODIS algorithms for a variety of land-cover products; the most notable of which are vegetation indices, land-cover, LAI and NPP. MODLAND has established multiple field sites that gather a variety of field measurements from specific biomes used to calibrate their different products. Field sites are specific to different biomes and cover spatial scales congruent with MODIS resolutions (Cohen and Justice 1999). The BigFoot project is charged with validating MODLAND products with independent datasets. In brief the project has established 5x5 km field plots representing various land-covers from which they can gather long-term data on numerous variables related to carbon fluxes (Running et al. 1999). These variables are compared with derived NPP results in order to validate the MOD17 product.

The MOD17 product is an evolving dataset. As significant modifications are made the entire series is re-run. The current iteration of the algorithm is version 4.5. This version makes valuable modifications to the interpolation of meteorological data for integration with MODIS imagery. Light-use efficiencies have been modified based on current field research. Finally, the algorithm is based on eight-day GPP summations rather than the previous 16-day summations. This increases the sensitivity of NPP but also introduces a greater potential for cloud contamination. Zhao et al. (2006) provides further details on these algorithm modifications.

MODIS is a relatively new sensor and data first became available in 2000. A six-year period between 2000 and 2005 currently represents the entire MOD17 dataset. Texas lies at the intersection of six MODIS scenes so all six scenes for the six years of the MOD17 dataset were acquired from the MODIS ftp site (ftp://ftp.ntsg.umt.edu/pub/MODIS/TERRA/Tiles/MOD17A3.105.LATEST/). For each year, all six scenes were mosaiked together and projected to UTM zone 14, NAD83. After this, Texas was then cut from the mosaics and all years were averaged to produce the final NPP product (Figure 5). This was done to help normalize any inter-annual variability caused by seasonal shifts, extreme climatic events, or miscalibration of the radiometric sensor.

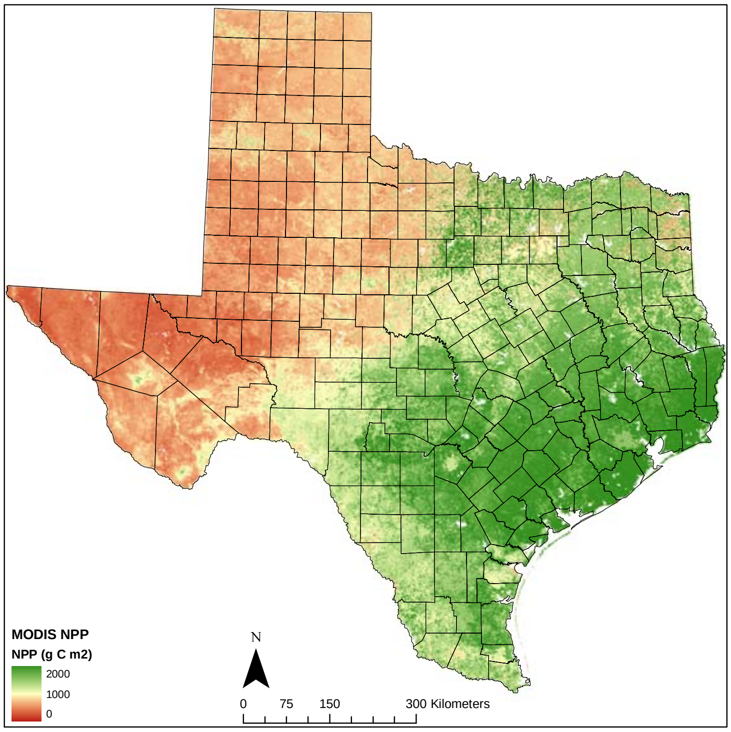


Figure 5: Average MODIS NPP_{act} between 2000 and 2005 for Texas.

There were several adjustments that were made to the mosaics to try and achieve high levels of uniformity. The MOD17 product has several fill-codes that mask areas. These pixels are urban/ built-up areas, inland fresh water bodies, and a few barren or sparsely vegetated pixels. By examining the masked pixels it became obvious that they were static between years; that is they do not change over time. To achieve a complete coverage of NPP these masked pixels were re-calculated and populated with estimated NPP values. If a pixel is classified as 'barren' it is assumed to not produce NPP, as vegetation is either extremely sparse or not present. All such pixels are in west Texas where their neighboring pixels have very low NPP values. Because surrounding pixels were of such low value and the masked pixels classified as barren a simple reclassification was preformed with resulting pixels having a value of zero (0) NPP. Pixels classified as water were left masked. The rationale behind this is that the methods for calculating $NPP_{aquatic}$ differ significantly from terrestrial NPP (Field et al. 1998; Peterson 1980). Secondly, inland aquaculture is a relatively minor activity performed on only a handful of these masked pixels. Finally pixels masked as urban were filled by averaging the values of their nearest unmasked neighbors. After examining the location of these masked pixels with reference to a selection of large and small cities, it was determined that they poorly represented actual urban areas; i.e. the extent of masked urban areas does not reflect their actual real world extent. Although no literature could be found which explains the methodology behind masking urban/built-up pixels in MODIS processing, it is hypothesized they use an out-of-date land-cover mask. This provides advantages in filling these urban pixels because the actual extent of contemporary urban areas lies outside the masked pixels. Therefore, because the surrounding urban pixels can be assumed to have similar values as masked urban pixels an average of nearest neighbors provided appropriate NPP values to 'fill' the urban areas.

From this final dataset actual NPP values were calculated as three different products. The first is actual NPP in g C m^{-2} (Figure 5). This shows the spatial variations of NPP across the state. Spatial patterns can be derived from this product relating to natural and human features such as cities or rivers. The second product is total NPP per county. This is simply the sum of carbon produced in a county and was used to compare with harvested NPP. The final product is total available carbon per county. This product was useful for comparing crop production to available carbon per county.

Timber Statistics

Timber statistics were derived from two sources. The most important are logging statistics kept by the Texas Forest Service. Secondly, there are statistics kept by the agricultural census (discussed below). Yearly reports from the Texas Forest Service publish harvest trends for major timber-producing counties and facilitate the interpretation of trends in wood markets and management techniques (Xu 2001, 2002, 2003, 2004, 2005, 2006). These trends cover fluctuations in market prices for timber products, estimates of residues from logging and milling and, most importantly, the volume of timber harvested for different markets as sawn timber, veneer and paneling, pulpwood, and poles. These parameters are further broken down into products derived from pine and those from hardwood. Finally data are also recorded for industrial timber, which is the volume of timber removed from the forests prior to milling (Xu 2006a).

As outlined in the modeling section, there is no need to account for milling losses because industrial timber is pre-milling. However, the harvest index (logging residue) does need to be calculated. Logging residues include tops, limbs, leaves, and stumps but not root mass (Xu 2006b). Beginning in 2003 the Texas Forestry Service has calculated the amounts of biomass lost through logging (Xu and Carraway 2005). These calculations are made for the region as a whole and therefore are not directly transferable to the county-level analysis. Therefore to calculate logging residue by county (LR_i in equation (6) Timber Production), average total industrial timber was divided by average total logging residue for every reported year (2003-2005) for both pine and hardwood. This value was then divided by the industrial timber production for each county which yielded logging residues for each county in cubic feet.

$$LR_i = \frac{PC_i}{\left(\frac{\sum PC_i}{\sum RR_i}\right)} \qquad \text{(9) Logging Residue}$$

where PC_i is reported production for each *i* (pine or hardwood) in every county, divided by statewide production ($\sum PC_i$) over statewide reported residue ($\sum RR_i$). In Texas LR_i for pine and hardwood are 7.0 and 3.7 respectively. See Appendix A: Model Parameters for specific values for each input. Finally for this data to be comparable to the MODIS NPP six-year composite product the above methods are applied to each year's timber data and averaged.

Crop Statistics

The National Agricultural Statistics Service (NASS), part of the U.S. Department of Agriculture (USDA), collects data on agriculture and agriculturally-related variables. There are two resources utilized from the USDA NASS in the production of these statistics. The first product is based on yearly sample population surveys and the other is the agricultural census.

ANNUAL CROP SURVEYS: Samples are collected every year by individual states to survey crop and livestock production in each county within every state. There are a number of methods used to achieve this goal including mail surveys, telephone interviews, in-person interviews, and field observations. Prince et al. outline the main two methods: area frame surveys and list frame surveys (2001:1195-1196). Area frame surveys use remotely-sensed imagery to segment the landscape into roughly one square mile grids. Enumerators then visit a random sample of these grids to record the agricultural activities. List frame surveys rely on random sampling from a contact list of all producers and other agribusinesses (e.g. feed lots and grain elevator operators). These individuals are contacted and enumerators administer a survey regarding current conditions as well as intentions for the remaining season. Estimates are calculated based on both the field sampling and surveys, and are cross-referenced with other industry surveys to help validate the results (NASS 2005). Since this is a sampling method the data is subject to sampling errors. Prince et al. report sampling errors for the area planted of between 1-5% for selected crops (2001:1196).

To minimize the amount of time that farmers take responding to these surveys, they only focus on each state's major economic agricultural industries. For Texas this includes different types of livestock husbandry and major grains. It does not include other major agricultural crops such as citrus, watermelon, and pecan. In depth descriptions on each crop can be found on the USDA NASS website (http://www.nass.usda.gov/Census/Helpfile/US_AppendixA.htm#6).

AGRICULTURAL CENSUS: The agricultural census data is used in this study to account for crops not covered by the annual surveys. The census has been ongoing for over 160 years (1840-2002) on a 5-year cycle (USDA 2004a:VII). It employs similar techniques to the annual surveys but seeks greater coverage of crops and farmers, and used a larger sample size. The census mailing list is the foundation, and it contains an up-to-date record of all farmers. Every attempt is made to ensure its accuracy. Everyone on the mailing list receives one of two forms (a sample or non-sample form) (USDA 2004a:C-1). The sampling system used is based on the number of farms per county, and this determines how many individuals receive the sample form (an adjustable rate ranging from one in two for counties with 100-200 farms to one in eight for counties with more than 400 farms). Those individuals not receiving the sample form get the non-sample form. Sample forms contain questions on types of crops, amounts, and yields; whereas the non-sample form also contains questions about management technologies (i.e. fertilizers, machinery, labors) (USDA 2004a:C-2). Non-respondents are sent the form a second time to improve response rates. Returned census forms are processed using an elaborate set of methods to ensure data integrity. For example, if one respondent reports planting five acres of wheat but fails to indicate harvest yield a nearest neighbor algorithm pools similar (demographic and spatial) candidates for a replacement value.

Finally this data is cross-referenced with area frame surveys following the same methodology as the annual surveys.

USDA NASS recognizes that their coverage is not complete and therefore implements adjustments to compensate for this. Not all farms are included in the mailing list for reasons such as they are new, the person has moved, the address is incorrect, or the farm has been bought or sold. Fieldwork from the area frame survey is used to develop calibration variables that estimate under-coverage by the census. These algorithms use a linear truncated method based on a restricted regression equation that assigns weights to specific variables to adjust the final coverage (USDA 2004a:C-9).

USDA NASS also recognize unquantifiable errors such as data lost/not reported by farmers or entered incorrectly by enumerators (USDA 2004a:C-6). Although they offer sources for the error ("respondent or enumerator error, incorrect data capture, editing, and imputing for missing data" (USDA 2004a:C-6)) there are few methods available to correct them.

The final source of error for both the census and the annual surveys is interpreting the data; in particular the meaning of zero (Hicke, Lobell, and Asner 2004:5-7). There are four codes used by USDA NASS that are numerically zero, although they may not actually be zero. First is an actual zero, where a particular crop may have failed and therefore production may actually be zero. Second, recorded as "(Z)" in the raw data, represents a number that is less than one half the reported unit, therefore the value is rounded to zero. Third is “(NA)” and corresponds to data not published. In most instances this is historical data that cannot be compared to current values due to changes in methodology. Finally “(D)” is coded to mask data and avoid disclosing information on individual farmers. If there is only one reporting farmer in a county USDA masks that data for confidentiality (USDA 2004a:IX).

Data Categories

For organizational purposes crop data is divided into five categories: grain, ‘other field crops’, hay, vegetables, and fruit. Most crops are straightforward and only require finding crop- and biome-specific conversion variables. This is accomplished by consulting previous HANPP studies, particularly those using USDA NASS data (Hicke and Lobell 2004; Hicke, Lobell, and Asner 2004; Lobell et al. 2002; Prince et al. 2001) or agricultural publications (Donald and Hamblin 1976; Hay 1995; Martin, Leonard, and Stamp 1976; Pinto, Bernardes, and Pereira 2006). In a number of cases another variable is added, yield, which can be found in these same sources. With yield, acres harvested (the published statistic for most fruits and vegetables) can be converted to total production, and harvested NPP can then be calculated.

A few preprocessing steps are used to prepare the USDA NASS data. Annual surveys do not report all counties for every crop and every year. The sampling design occasionally misses counties or confidentiality requires masking the data (Hicke, Lobell, and Asner 2004). Fortunately the annual surveys report not only county-level statistics but also at regional levels roughly equivalent to the Texas ecoregions. Where incomplete, county data is supplemented with regional data. Regional data is spatially distributed across the region's counties. This can be done within a GIS environment proportionally based on each county's area thereby giving larger counties a greater proportion of the regional crop produced.

A second preprocessing step averages annual data. Data from the annual surveys are treated with the same averaging technique as the MODIS data. Not only will this match the temporal period of MODIS but it will alleviate inter-annual variations in the dataset. Therefore data is collected for all reported crops, for all counties, and all years (2000-2005), then averaged producing one dataset per crop.

Finally, a good deal of crop data reported in the 2002 agricultural census is reported only in acres harvested and not total production. A new variable is introduced, yield, which is the amount of crop produced per acre. This is a single variable for each crop type specific to agricultural patterns in Texas. Yield is multiplied by harvested acres to give total production. Although this is not ideal as yield values can still vary across the state, it is the only available method to convert the census data to harvested NPP. Crop-specific yields were obtained from similar resources as conversion factors and are reported in the crop tables in Appendix A: Model Parameters.

GRAINS AND OTHER FIELD CROPS: Grains are the most widely reported of the crops. A complete list of both grains and 'other field crops' (a category defined by USDA) can be found in Appendix A: Model Parameters. Crops are considered similar if they exhibit similar growing, harvesting, or are reported in a like manner. An outlier in this category is sugarcane. Modern harvesting of sugarcane involves burning cane blades followed by reaping the cane, but the root mass is left alive and intact (Martin, Leonard, and Stamp 1976:424). As a result new cane will re-grow from the original root mass. Martin estimates that after approximately ten harvests, diminished returns facilitate completely new plantings. The fraction of aboveground matter to below therefore approaches one (1) and assumes that the harvest of root mass is negligible (i.e. ten harvests per one root mass). The remaining grain crops are straightforward in that Prince's model was formulated for this type of data and conversion factors are readily available.

HAY: Hay is also simply calculated using equations (4) Crop Production, and (5) NPP. Included in this category are hay, silage, and forage. There are a variety of different grasses grown for hay such as alfalfa, clover, and wild hay (Martin, Leonard, and Stamp 1976:220). Silage and green crop are fermented plant products that are highly nutritious and efficient to produce. Silage, and particularly corn silage, utilizes all of the plant parts (ear, leaves, stocks) to produce feed for livestock (Martin, Leonard, and Stamp 1976:231). Because the entire aboveground part of the plant is used the harvest index for this category is one (1), and for silage the moisture content is quite high for fermenting (Lobell et al. 2002:725). The different types of crops for the hay category and their conversion values can be found in Appendix A: Model Parameters.

VEGETABLES: Due to reporting differences vegetables are broken into two groups that are dealt with separately (Appendix A: Model Parameters). The first group are crops for which USDA NASS reports total production. These are predominantly legumes. These data is easily integrated and converted to harvested NPP. The second group, mostly leafy or garden type crops, is reported by acre harvested. An additional variable, yield, is required to calculate total crop production, which in turn is used to calculate harvested NPP.

FRUITS: The final group comprises fruit crops. Fruit crops are unique in that they are perennials and mostly orchard crops. Converting these crops to harvested NPP offers specific challenges. First one must consider that the whole plant is not harvested, only the fruit and second, because the plant is not destroyed root turnover does not occur simultaneously with the annual harvest. Harvest index therefore approaches zero (0) because only a very small percentage of the plant is harvested and the same plant continually produces fruit. The fraction of aboveground biomass harvested approaches one (1) for the same reason as sugarcane (i.e. the root mass is not harvested with the crop) as shown in Appendix A: Model Parameters. Fruit crops are also reported as acres harvested and must therefore be converted using yield to compute production.

CHAPTER IV

RESULTS

This chapter presents the results of human appropriation of net primary productivity for the state of Texas. It begins with the overall results for the state, comparing actual NPP (Figure 5) to total agricultural and timber production to calculate the difference (HANPP). The chapter then presents results from each major agricultural or timber group: (i) timber industry, (ii) grain, (iii) 'other field crops', (iv) hay and silage, (v) vegetables, and (vi) fruit. Within each major group the results for different crops are presented. The included crops are either keystone crops for that group or ones that reveal interesting spatial patterns. Tabular results for all crops can be found in Appendix B, while maps of NPP and production for crops not presented in this chapter may be found in Appendix C.

Totals

MODIS Results

The MODIS-derived NPP estimates fit the anticipated spatial pattern of NPP for Texas; being highest in the southeast and lowest in the northwest (Figure 5). The pattern, as already noted in Chapter II, is mainly controlled by availability of moisture. A simple comparison of annual average rainfall (Figure 6) and average NPP per county (Figure 7) illustrates this relationship very well. In line with other regional predictions of NPP (Hicke et al. 2002) Texas shows low levels of NPP in west Texas where there is little rainfall, high temperatures, and high evaporative demand. NPP is higher in the Panhandle due to lower temperatures and irrigation from the Ogallala aquifer. Across the Edward's Plateau and Blackland Prairie in the middle of the state NPP increases further, due to increased rainfall, and decreased temperatures which lower evaporation rates. NPP in the Rio Grande Valley is high due to lowered temperatures, increased rainfall, and a very strong human influence. The highest NPP values are found along parts of the Gulf Coast and in east Texas where precipitation is high and evaporation relatively low, as evidenced by highly productive cultivation (Figure 8) and large forested areas. In all, total carbon production for the state is 268 million tons, with a per county average for NPP of 400 g C m^{-2} yr^{-1}.

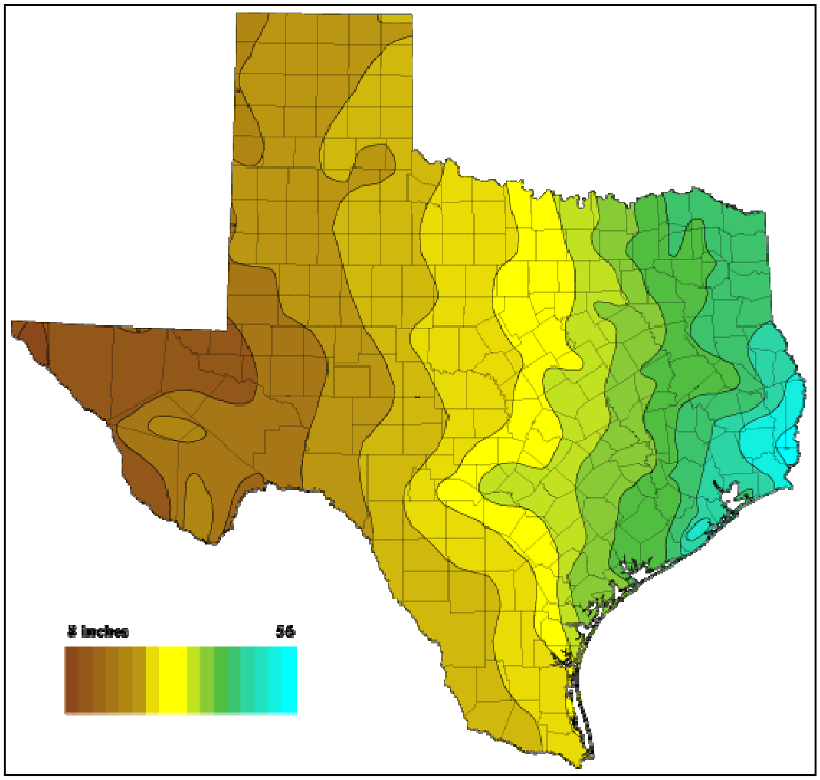


Figure 6: Texas mean annual precipitation (Texas Parks and Wildlife Department 2008).

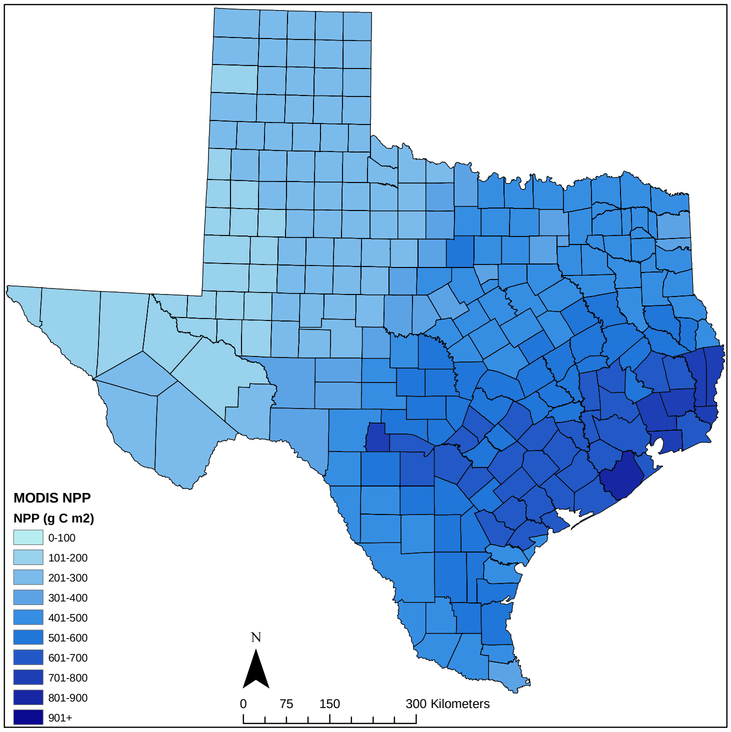


Figure 7: Average MODIS NPP_{act} between 2000 and 2005, averaged per county.

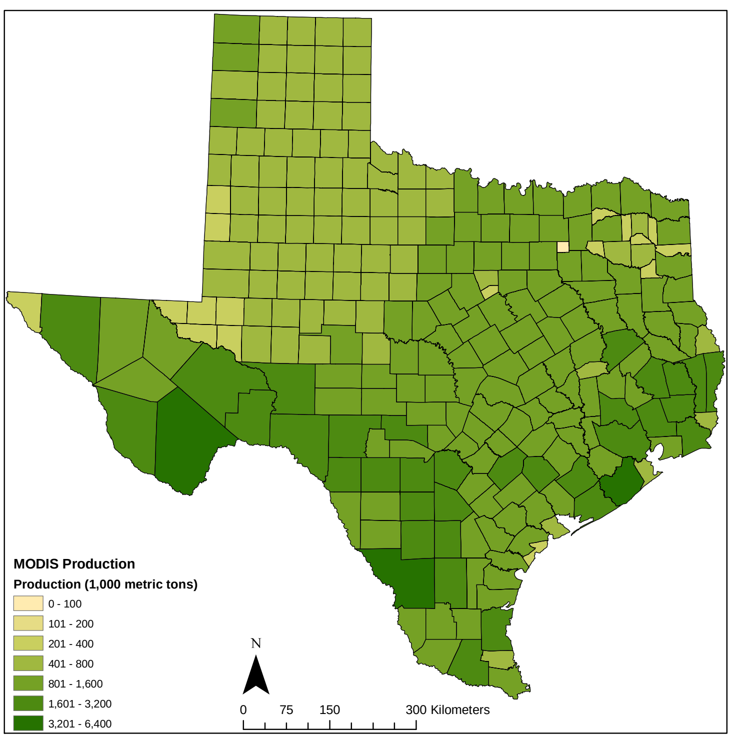


Figure 8: Average production of carbon between 2000 and 2005.

Figure 8 shows total carbon produced (the average from 2000 to 2005) per county, as both a function of plant efficiency, and county area. Large counties in west Texas (e.g. Pecos or Brewster counties) produced the most carbon over this time even though NPP in west Texas is quite low. In a similar vein, small counties in northeast Texas (e.g. Rockwall, Franklin and Morris) have low total carbon production values, not because NPP is low but due to their small areas. Nonetheless by comparing similar size counties such as Jasper and Newton (well-wooded counties in east Texas), Hidalgo (in the Rio Grande Valley), and Dallam and Hartley (in the Panhandle) where agriculture is very well-developed, it is clear that differences in carbon produced are due to high differences in production efficiencies (NPP) due to a combination of natural and human processes.

Rockwell County produced the least amount of carbon (137,000 tons) and Webb County in the Rio Grande Valley produced the most (approximately 4 million tons) (Table 2). Considering productivity (NPP) Brazoria County in the Gulf Coastal Plains had the highest NPP (888 g C m^{-2} yr^{-1}) while El Paso County in west Texas had the lowest (123 g C m^{-2} yr^{-1}). Even though Webb County was more than twice the size of Brazoria, agriculture and natural vegetation in Brazoria County was twice as efficient in terms of NPP and therefore produced almost the same amount of carbon.

Table 2: NPP and production averages between 2000 and 2005 for select counties. Excerpted from Appendix B.

NAME	Area (km2)	NPP (g C m^{-2} yr^{-1})	Production (1,000 tons C)
Rockwell	385	355	137
El Paso	2,656	123	327
Brazoria	3,856	888	3,424
Webb	8,740	447	3,905

Agriculture and Timber

The NPP of harvested crops is not straightforward. Figure 9 shows low values of NPP. This is because total NPP is for the all harvested carbon from all crops in a county divided by total area for that county. It is very unlikely that crops cover entire counties (or even large proportions of many counties). However it is difficult to determine the actual total area for all crop types in any given county for the following reasons. Both inter-cropping and multiple growing season increase the apparent areas under agriculture as reported by USDA statistics because the same parcels of land get counted multiples time (per cop type or harvest). Agricultural census returns for fruits and vegetables are reported in area cropped, and presented methods use a constant yield for each fruit or vegetable. As a result, crop efficiency – NPP – is constant for each fruit or vegetable across the state negating any useful information on spatial variations in NPP for those crops.

Therefore, it is more illustrative to examine the total amount of carbon harvested from crops per county rather than square meters (Figure 10). In total, 28.8 million tons of carbon was harvested from agriculture and timber based on the 2000-2005 averaged data. Two competing trends emerge from this data. The first and most obvious is that harvested carbon coincides with regions of naturally high NPP (e.g. Gulf Coast Plains and east Texas). The second trend is driven by socioeconomic variables particularly related to irrigation technology and corresponds to high production areas like the Panhandle and the Rio Grande Valley.

Hidalgo County, in the lower Rio Grande Valley, harvested the greatest amount of carbon (an average of 914,000 tons from 2000 to 2005) due to its highly managed and well irrigated fruit and vegetable production. Rains County, in northeast Texas and the fifth smallest county, harvested the least amount of carbon (1000 tons) which equates to only 0.25% of that county's primary productivity.

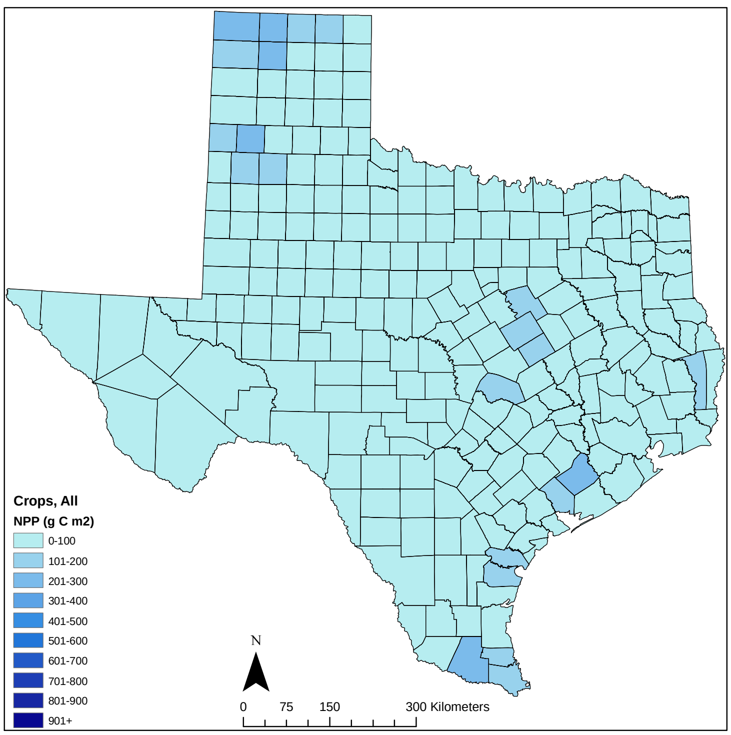


Figure 9: Average NPP from all harvested crops and timber between 2000 and 2005.

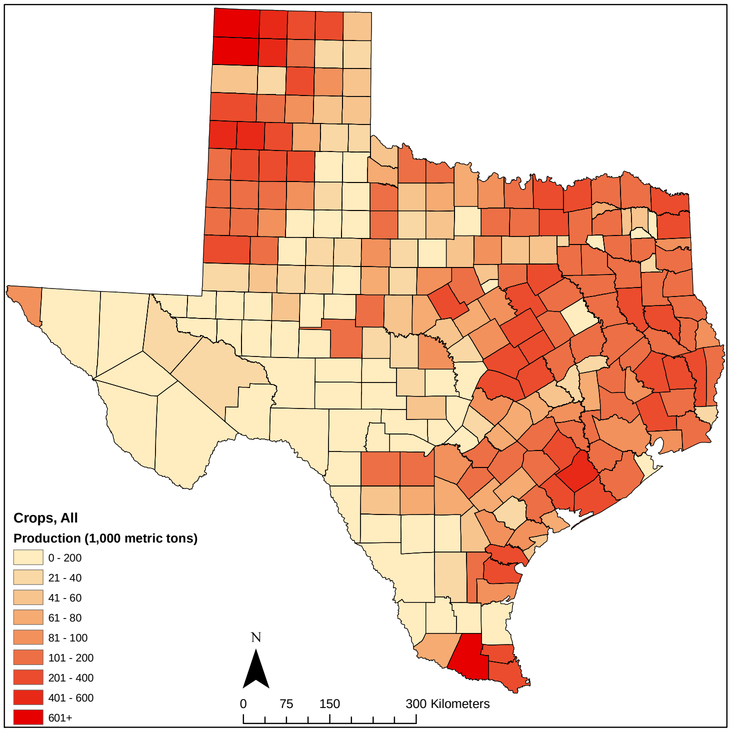


Figure 10: Average production of carbon from all crop and timber between 2000 and 2005.

HANPP

HANPP is the ratio of total available NPP and harvested NPP (see Chapter III). Average HANPP for Texas is 13.13% (Figure 11). For the majority of counties (156 of 254) humans appropriate less than 10% of NPP. However ten counties appropriate greater than 50% of available NPP (Table 3). Most of these ten counties correspond to counties dominated by field and grain crops in the Panhandle while the others are dominated by fruit and vegetable crops (Hidalgo, Willacy, and Cameron). There are also signs of the impact of major urban areas on neighboring counties (Wharton and Waller counties near Houston; Collin and Rockwell counties near Dallas; and Williams north to Ellis County along Interstate 35 between Austin and Dallas). Increases in agricultural and timber industries, to meet the demands of these urban corridors, lower HANPP furthering the impact of urban structures on the environment. That is, demand increases the spatial extent of these activities and more importantly drives intensification, harvesting more carbon.

Table 3: The ten Texas counties with highest HANPP from 2000 to 2005. Excerpted from Appendix B. Sherman County (101.27%) can be explained by the research method's margin of error.

NAME	HANPP (%)
Sherman	101.27
Moore	93.35
Dallam	92.97
Castro	92.03
Hartley	82.99
Parmer	76.97
Hansford	62.26
Hale	58.86
Lamb	56.88
Ochiltree	56.58

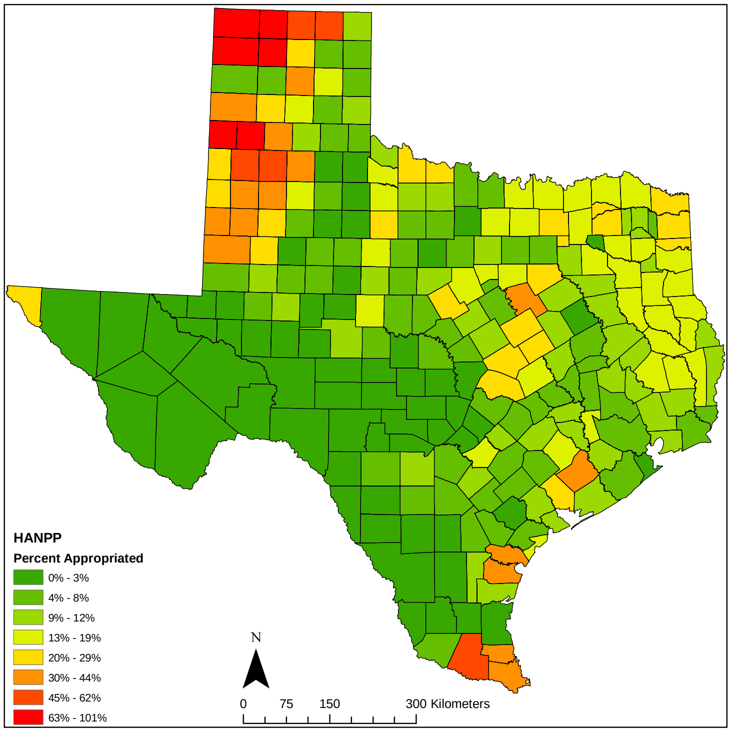


Figure 11: Average HANPP between 2000 and 2005.

Timber Industries

All timber industry practices account for the extraction of 3.5 million tons of harvested carbon in Texas. This represents 12% of all harvested carbon and is almost exclusively contained in east Texas (Figure 12). Average carbon harvested is 66,160 tons per county, with Jasper harvesting the most (244,000 tons).

Timber (pine and hardwood) is exclusively confined to the east Texas forests (Figure 13). The vast majority of this harvest is cut for dimensional lumber, pole wood, plywood and veneer, and paper and pulp. It is harvested from national and state forests as well as private land but is well monitored by the Texas Forest Service (Xu 2006a). A notable exception to the east Texas spatial dominance in timber production is the growth and harvesting of Christmas trees (Figure 14). The spatial distribution of the Christmas tree harvest corresponds to nearby urban areas; counties like Travis and Bastrop serve the Austin metro area, while Montague, Wise and Denton counties serve the Dallas/Fort Worth metroplex. Houston also has nearby counties with a high proportion of Christmas tree farms serving its metropolitan area (i.e. Harris, Liberty and Hardin counties). Finally USDA provides data on short-rotation woody crops which are farmed at up to ten year intervals and serve as minor inputs to the paper and pulp industry. Spatially these crops follow the east Texas trend (Figure 15).

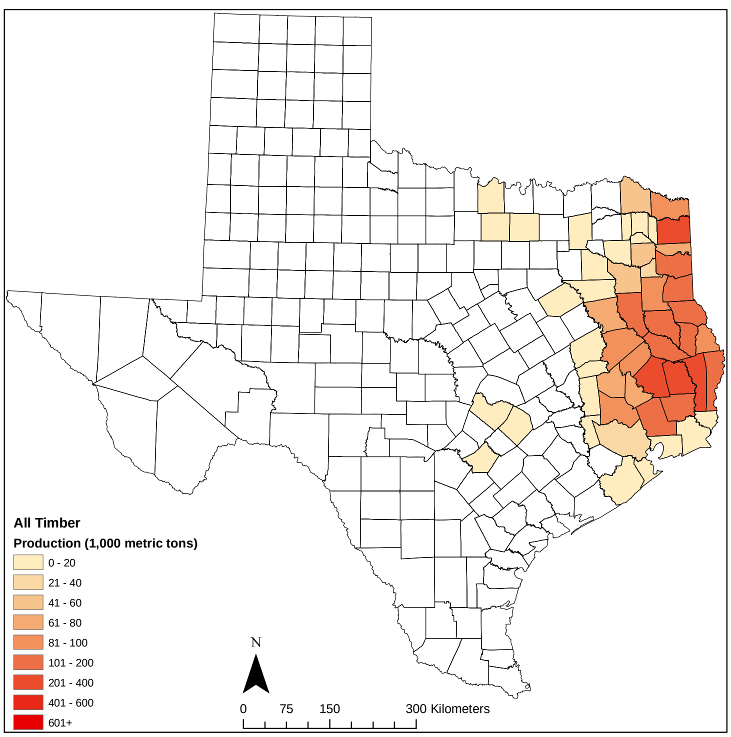


Figure 12: Average total carbon harvested from all timber industries between 2000 and 2005.

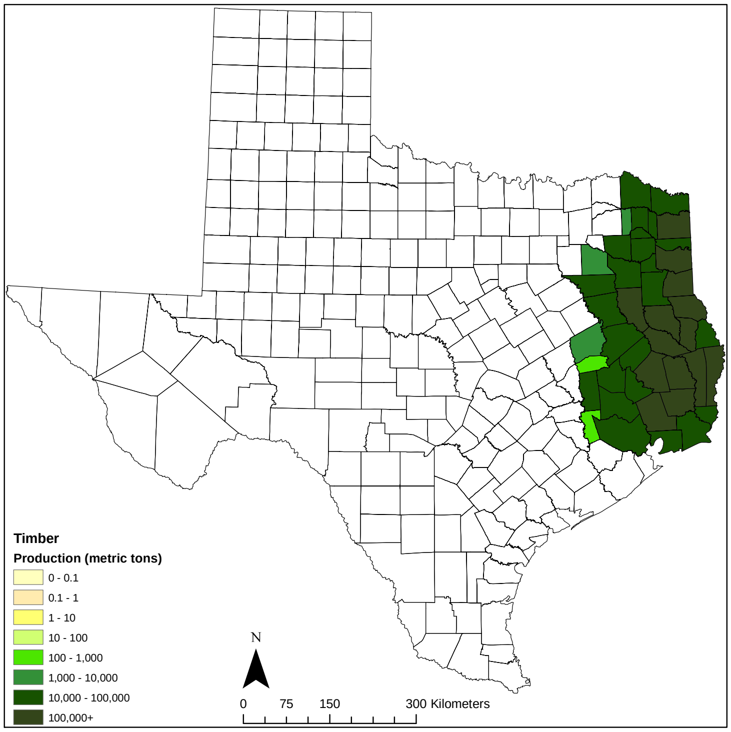


Figure 13: Average carbon harvested from pine and hardwood between 2000 and 2005.

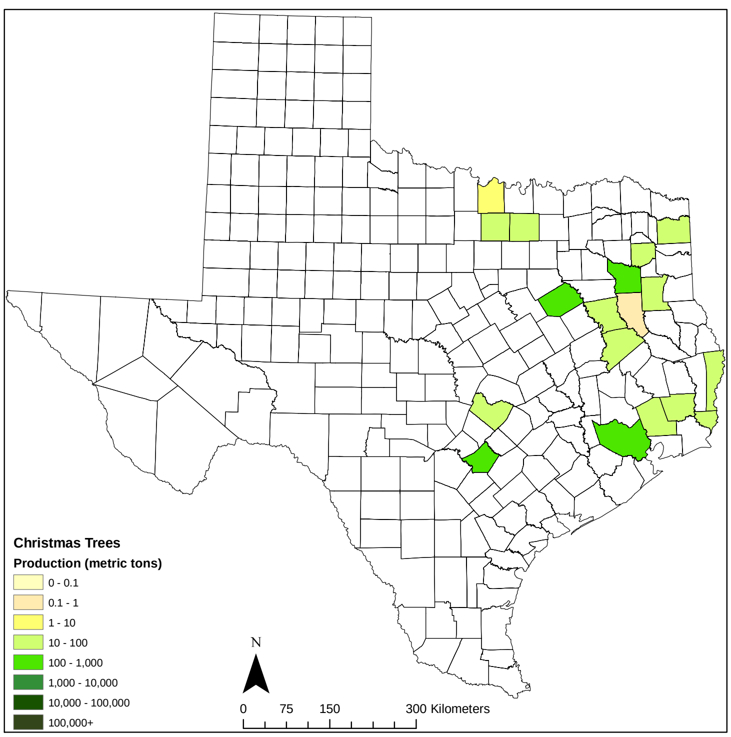


Figure 14: Average carbon harvested from Christmas trees between 2000 and 2005.

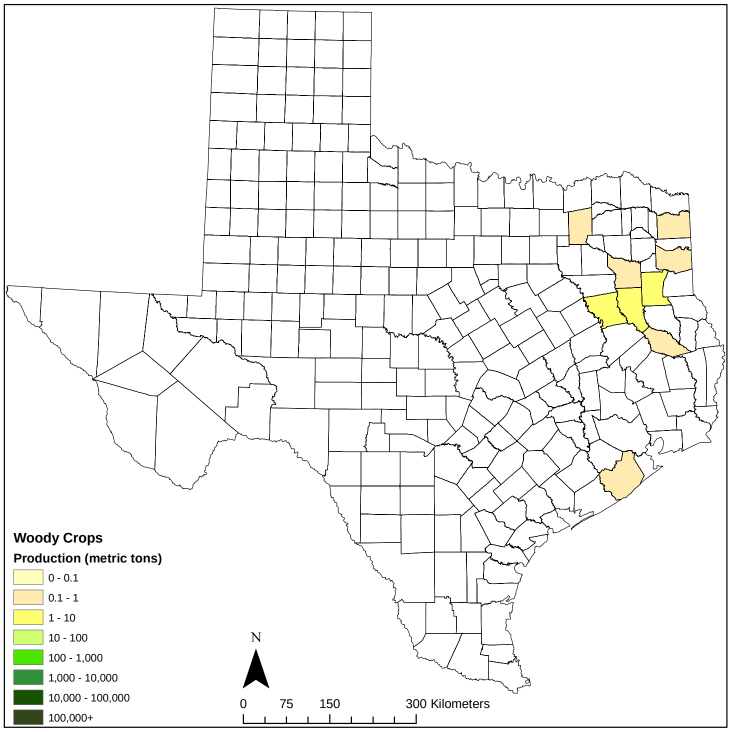


Figure 15: Average carbon harvested from short-rotation woody crops between 2000 and 2005.

Grain

Harvesting grain removes exactly 14 million tons of carbon from Texas. This equates to approximately 49% of all carbon harvested. There are strong spatial patterns in this data (Figure 16). The most dominant pattern is that of the vast acreages of corn, wheat and sorghum in the Panhandle. The overall average of carbon harvested per county is approximately 55,000 tons. In terms of grain the top five carbon harvesting counties are all in the Panhandle and each of them harvest over 480,000 tons of carbon per annum (Table 4).

Table 4: The top five counties for harvesting grain between 2000 and 2005. Excerpted from Appendix B.

County	Production (1,000 tons)
Dallam	819
Hartley	680
Sherman	569
Castro	487
Moore	481

A second spatial trend occurs along the Gulf Coast where corn, rice and sorghum are the dominant grain crops. A belt of corn, sorghum, and wheat parallels the I35 corridor from San Antonio to the Dallas/Fort Worth metroplex. There are also bands of agriculture in the Rolling Plains west of Dallas/Fort Worth and near San Antonio (these are predominantly wheat), and in the Rio Grande Valley (predominantly corn and sorghum).

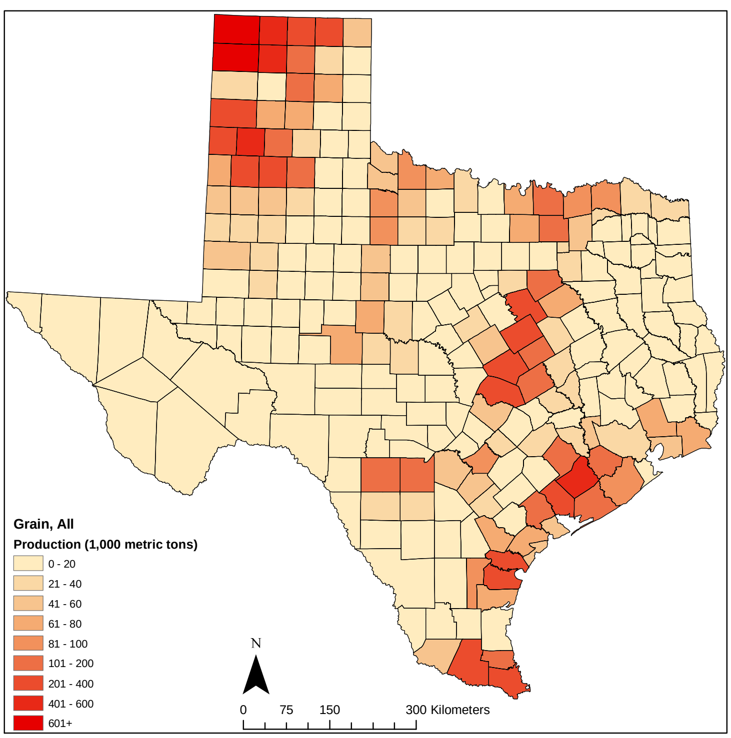


Figure 16: Average harvested carbon from all grain between 2000 and 2005.

Corn Grain

Carbon from corn harvested for grain is one of the main influences on HANPP in Texas. The dominant spatial pattern for this type of corn is similar to the total grains. There are belts of high corn production in the Panhandle, and along the Gulf Coast and I35 corridor (Figure 17). Furthermore there are regions in northeast Texas (along the Red River), south of San Antonio, and around El Paso where corn for grain is regionally high. Dallam and Hartley counties in the Panhandle harvest the most carbon from corn: 663,000 and 555,000 tons respectively. The average though is much lower at 22,000 tons.

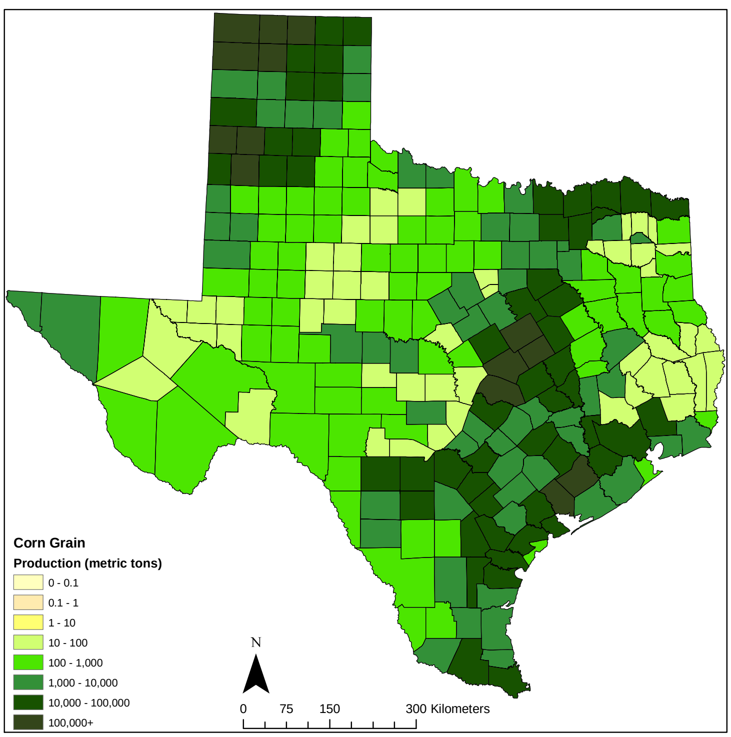


Figure 17: Average harvested carbon from corn for grain between 2000 and 2005.

Interestingly the efficiency, NPP, for corn is the opposite of the natural trend for NPP (decreasing as temperature and precipitation drop). While the natural trend in NPP is from southeast to northwest (Figure 7) it is opposite for corn (Figure 18). Instead of NPP being highest along the coast and diminishing northwards and westwards, the pattern for NPP_{corn} is that its generally high in the north and west. Average NPP_{corn} is 661 g C m^{-2}. NPP_{corn} is lowest in Kleberg County on the coast (219 g C m^{-2}) and greatest in Wheeler County in the Panhandle (1,341 g C m^{-2}). There are a few exceptions to the trend; there is Camp (northeast Texas), Tom Green (west Texas) and Cameron (Rio Grande Valley) counties.

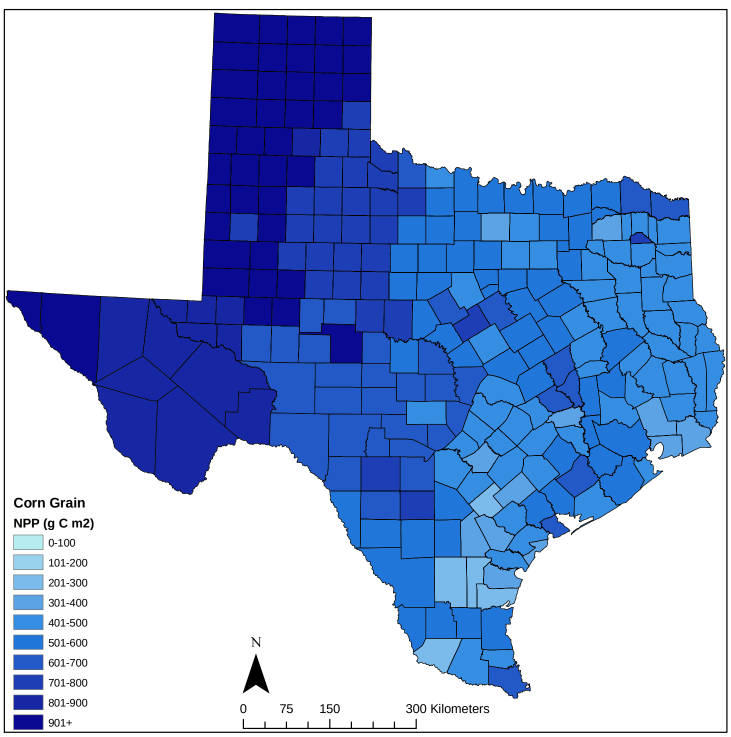


Figure 18: Average NPP of corn for grain between 2000 and 2005.

Oats

Oats are grown across the whole state, but production is greatest in the center (Figure 19). In total, 136,000 tons of carbon is harvested from oats. The average amount per county was 564 tons. Hamilton County in central Texas harvested the greatest amount at 11,000 tons. Production was least in the Rio Grande Valley where other crops dominate, east Texas where forests dominate, and west Texas where moisture is limited.

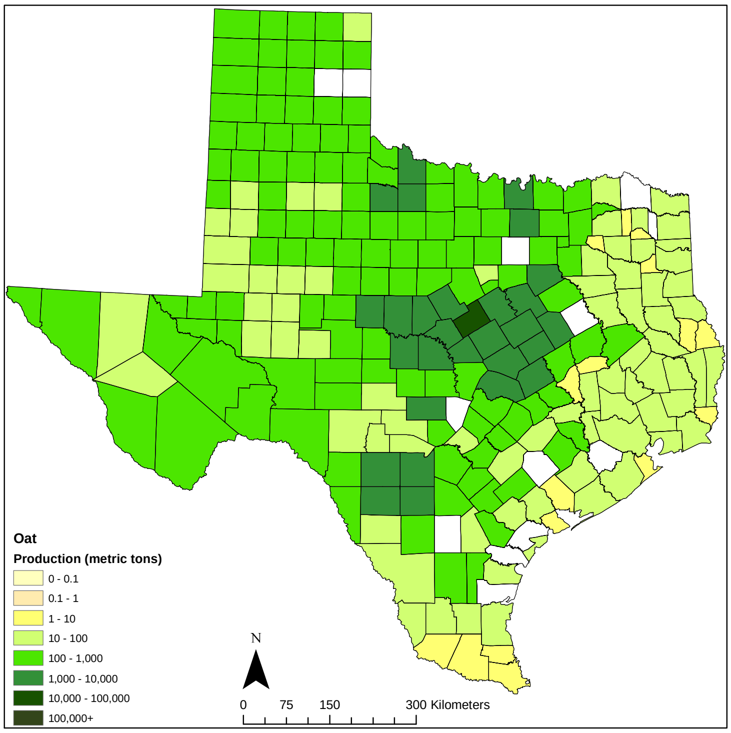


Figure 19: Average harvested carbon from oat between 2000 and 2005.

Rice

Rice requires high inputs of water and therefore cultivation in the state is limited to east Texas and particularly the upper Gulf Coast Plains where these demands can be met

(Figure 20). 830,000 tons of carbon is harvested. About a quarter of rice production comes from Wharton County (219,000 tons), and the average per county is 14,000 tons.

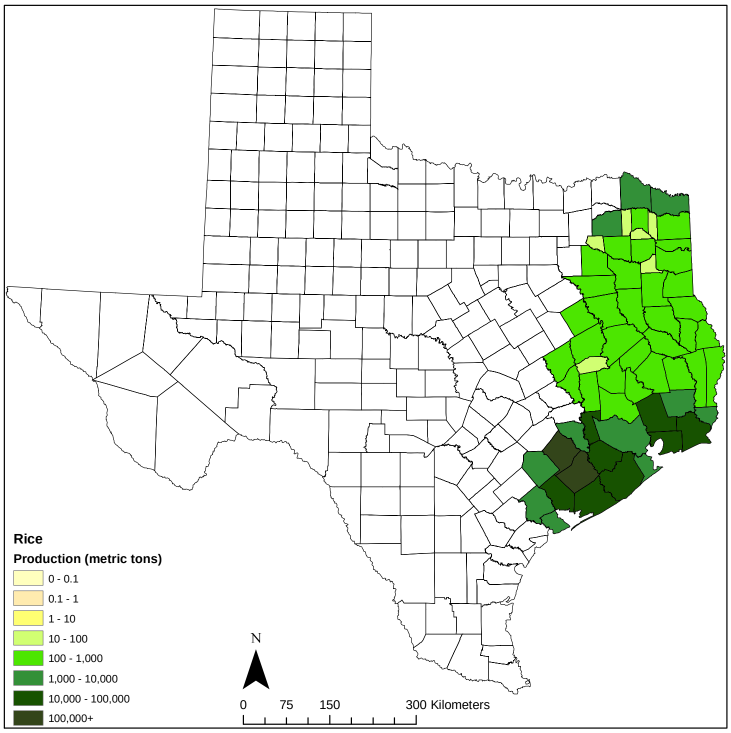


Figure 20: Average harvested carbon from rice between 2000 and 2005.

Sorghum

The spatial pattern of carbon harvested from sorghum is strikingly similar to that from corn for grain. Production is high in the Panhandle, between San Antonio and the Dallas/Fort Worth metroplex, and along the Gulf Coast Plains (Figure 21). Sorghum displays the intuitive trend in efficiency ($NPP_{sorghum}$) unlike corn for grain (NPP_{corn}). $NPP_{sorghum}$ is highest along the coast and lowest in the Panhandle (Figure 22). However, related to irrigation, there are areas where $NPP_{sorghum}$ oppose do not follow the trend (e.g. surrounding El Paso, south of San Antonio, and in the Rio Grande Valley). The average amount is 17,000 tons. In total 4.3 million tons of carbon is harvested from sorghum. Nueces, Hidalgo, and San Patricia counties have the highest carbon harvests for sorghum at 311,000, 226,000 and 204,000 thousand tons respectively.

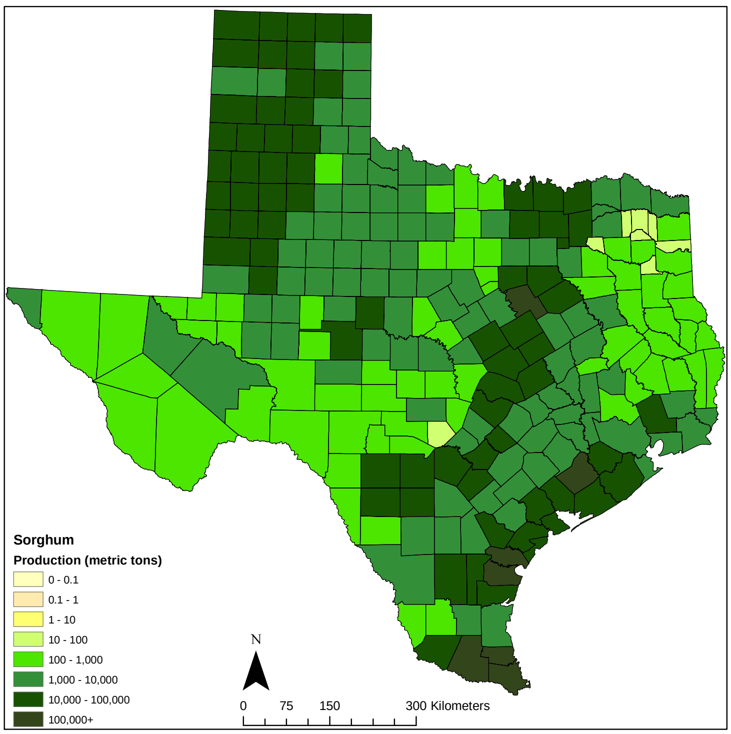


Figure 21: Average harvested carbon from sorghum between 2000 and 2005.

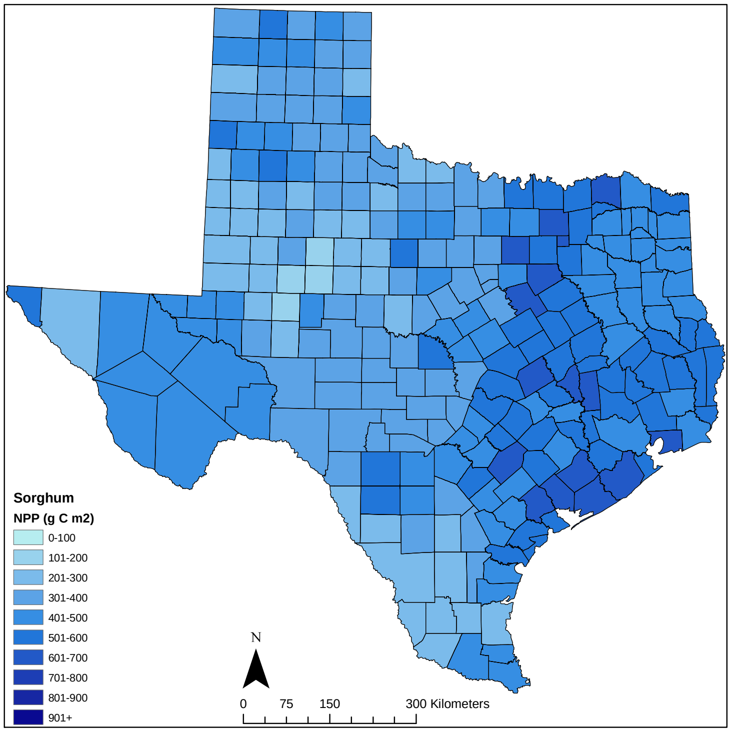


Figure 22: Average NPP of sorghum between 2000 and 2005.

Wheat

Wheat production is high in the Panhandle and along the I35 corridor. In this, its spatial pattern is similar to corn and sorghum (Figure 23). There is also a significant belt of wheat grown along the Rolling Plains (west of Fort Worth), and it is the only major crop situated in this area. Wheat can also be found along the Red River Valley in northeast Texas and south of San Antonio. To a lesser degree wheat is also grown on the upper Gulf Coast Plains adjacent to Houston. Harvested wheat is markedly lower in the Rio Grande Valley and in east Texas due to competing alternative crops. In total three million tons of carbon is harvested across Texas, and the county average is 12,000 tons. The top ten wheat producing counties are all in the Texas Panhandle (Table 5).

Table 5: The top ten counties for harvesting wheat between 2000 and 2005. Excerpted from Appendix B.

County	Production(1,000 tons)
Sherman	155
Hansford	133
Dallam	129
Ochiltree	114
Parmer	104
Castro	103
Deaf Smith	102
Hartley	93
Moore	90
Knox	89

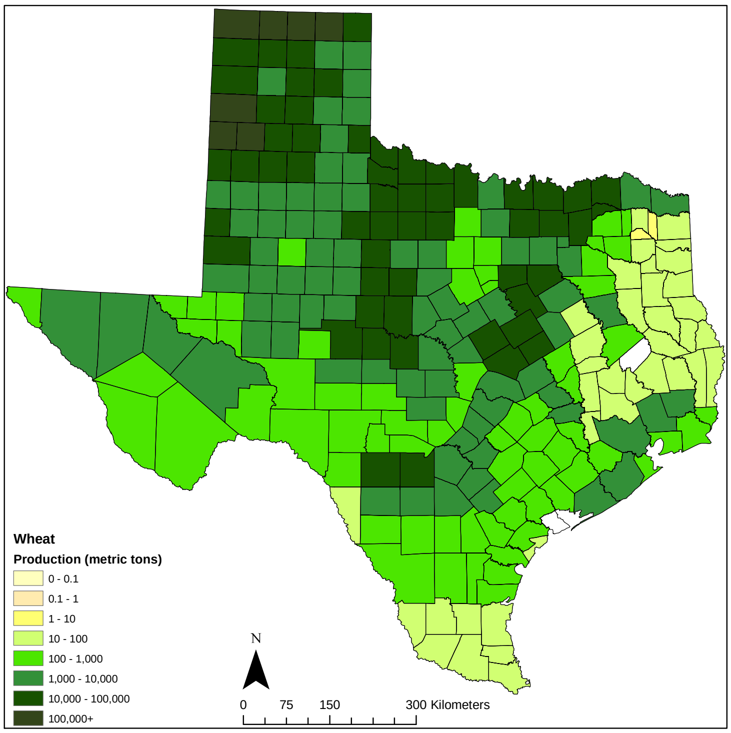


Figure 23: Average harvested carbon from wheat between 2000 and 2005.

Other Grains

Proso Millet is also grown for grain but is limited to Lubbock and Hale counties in the Panhandle. The total carbon harvested was 1,300 tons. Rye is also grown for grain, but is limited in area (only eight counties across the northern half of the state) and it harvests 6,000 tons. The spatial distribution of carbon production for these crops, as well as their NPP maps, can be found in Appendix C.

Other Field Crops

'Other field crops' (defined as any non-grain, non-hay field crop) consist of cotton, peanut, soybean, sunflower and some a few other minor crops. In the Panhandle, around Lubbock, 'other field crops' are dominated by cotton and peanuts; in the Rio Grande Valley they are cotton, soybeans, and sunflower; while along the Gulf Coast Plain cotton and soybean dominate (Figure 24). Nine percent, or 2.6 million tons, of all harvested carbon in Texas is from 'other field crops'. Gains County in the Panhandle harvested the greatest amount (231,000 tons) while the average for 'other field crops' was 10,000 tons.

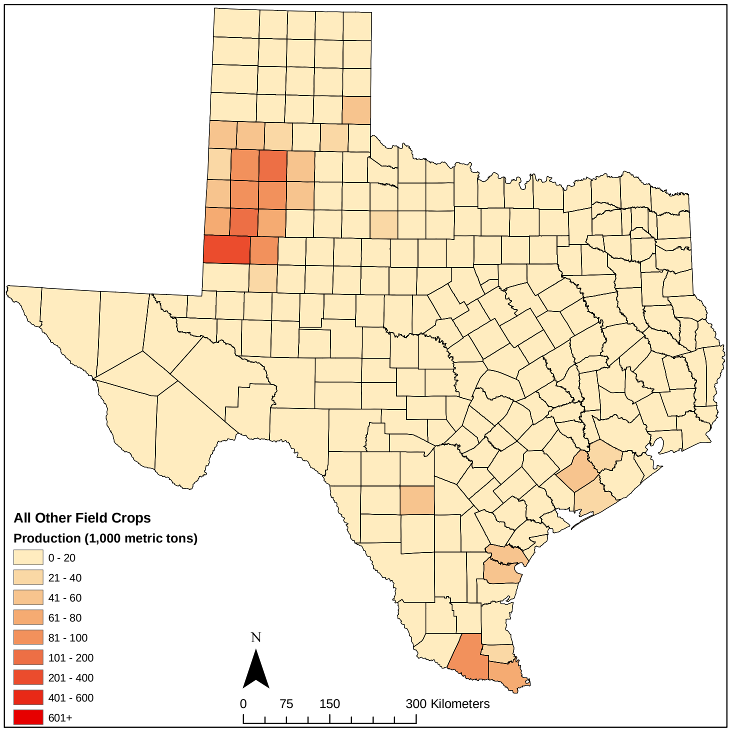


Figure 24: Average harvested carbon from all 'other field crops' between 2000 and 2005.

Cotton

USDA reports production data on two different types of cotton - American Pima and American Upland. Pima cotton is a hardier variety, better suited to arid growing conditions. Therefore pima cotton supplants upland cotton in west Texas (Figure 25). El Paso County which harvests 9,000 tons accounts for most of the statewide total 11,000 tons of carbon harvested from pima cotton. The average amount of carbon harvested per county was 790 tons.

Upland cotton is grown throughout the state. Regions of high production center around Lubbock in the Panhandle where management practices have increased the quality and value of the crop, and a belt extending from the Gulf Coast Plain to the Rio Grande Valley (Figure 26). There are, however, other regions of high production: west Texas, the Red River Valley, the I35 corridor and the South Texas Brush Country south of San Antonio. The average carbon harvested for upland cotton per county is 6,500 tons, with Hale County harvesting the most (105,000 tons). In total 1.6 million tons of carbon is harvested from upland cotton for the 2000 to 2005 averaged dataset.

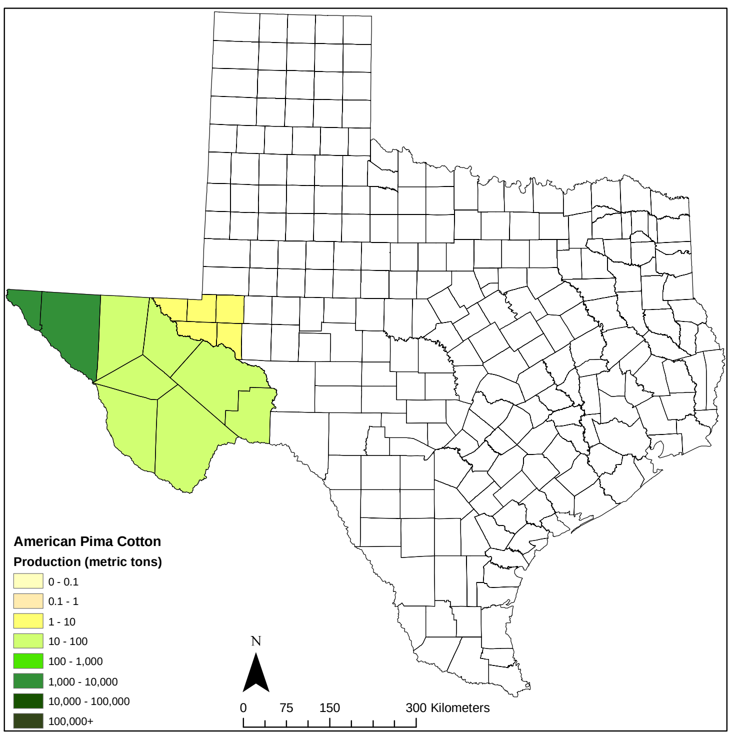


Figure 25: Average harvested carbon from American Pima cotton between 2000 and 2005.

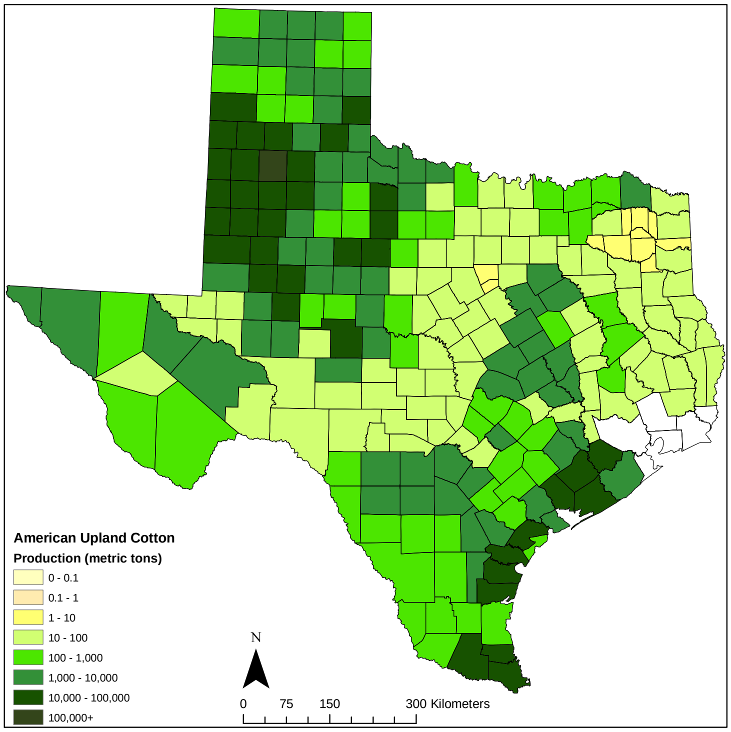


Figure 26: Average harvested carbon from American Upland cotton between 2000 and 2005.

Peanut

Peanuts grow throughout the state except west Texas and along the Gulf Coast (Figure 27). Production is highest in the southwest and central Panhandle and the Rolling Plains west of the Dallas/Fort Worth metroplex. Gains County harvested 148,000 tons of carbon while the statewide county average was 2,200 tons. Total carbon harvested from peanuts was 500,000 tons.

Peanuts are another crop that does not conform to the natural NPP pattern (Figure 28). There is a distinct north-south line from the Rio Grande Valley to the Panhandle. West of this line peanuts are not grown, while east it NPP diminishes.

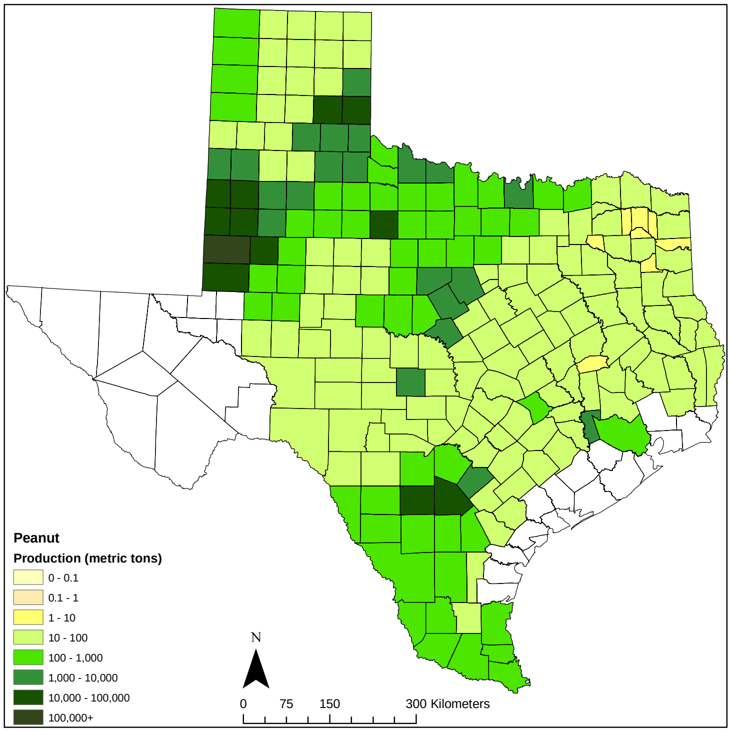


Figure 27: Average harvested carbon from peanut between 2000 and 2005.

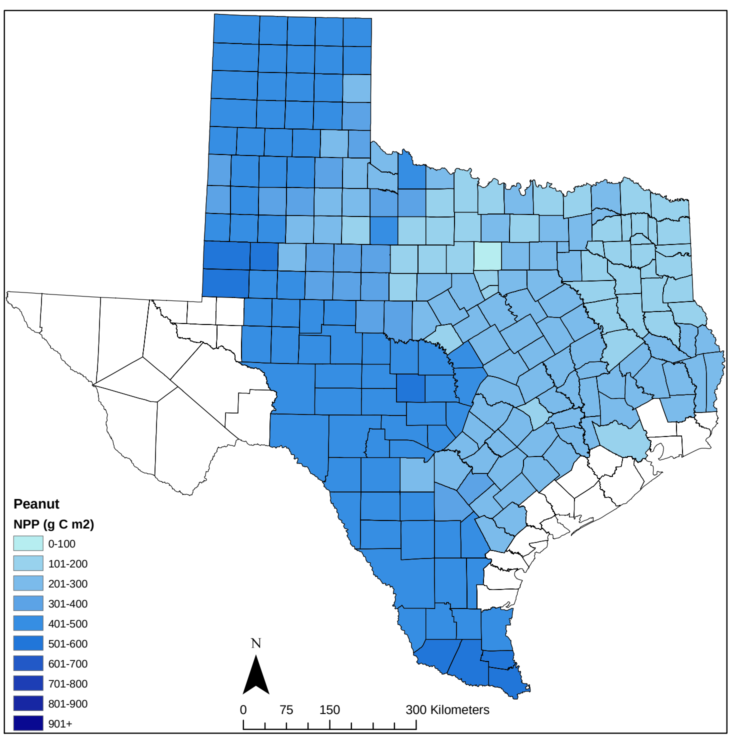


Figure 28: Average NPP of peanut between 2000 and 2005.

Soybean

Soybeans are grown extensively throughout the Panhandle, east Texas west to the Edwards Plateau (in particular along the Red River Valley) the upper Gulf Coast Plain, and the lower Rio Grande Valley (Figure 29). In total 245,000 tons of carbon was harvested from soybeans. Wharton County on the Gulf Coast Plain harvested the greatest amount (15,000 tons) while the county average was 1,500 tons.

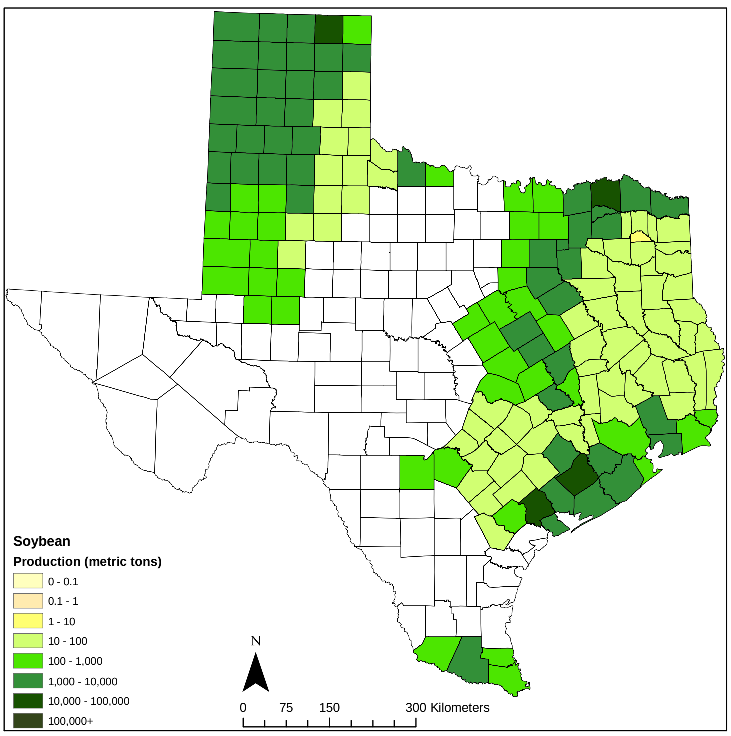


Figure 29: Average harvested carbon from soybean between 2000 and 2005.

Sunflower

The total amount of carbon harvested from sunflowers was 84,000 tons. Sunflower cultivation is restricted to a belt extending from the Rio Grande Valley through to the

Panhandle with an extension eastwards through the Hill Country to Burleson County (Figure 30). Production is greatest in the lower Rio Grande Valley and the western Panhandle. Cameron County harvested the greatest amount of carbon from sunflowers (7,000 tons), whilst Kendall County in central Texas harvested the least (4 tons). The per county average was 746 tons.

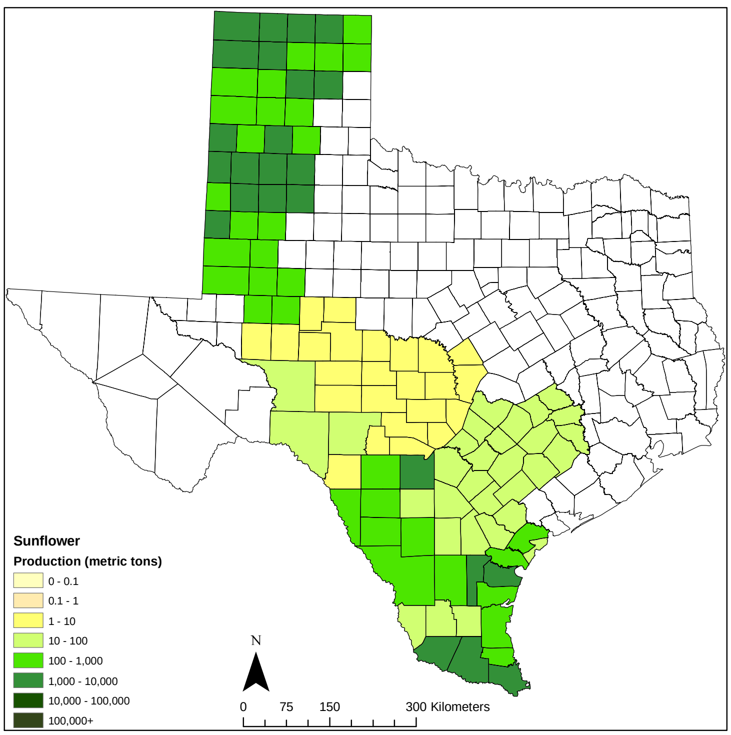


Figure 30: Average harvested carbon from sunflower between 2000 and 2005.

Other Field Crops

Miscellaneous 'other field crops' are not illustrated here but maps of their NPP and harvested carbon are available in Appendix C. These crops include sugarcane, beans, cowpeas, guar, peas, potatoes, and sweet potatoes. Although only grown in the Rio

Grande Valley, 121,000 tons of carbon was harvested from sugarcane. Bean distribution is patchy across the state with a total of 3,800 tons of carbon harvested. Cowpeas are grown in many of the same counties as beans and in total 546 tons were harvested. Guar is grown in the Rolling Plains west of Fort Worth, and in total 5,600 tons of carbon were harvested from the six counties in which it is cultivated. Four counties, all in east Texas, grew peas and combined they contributed 28 tons of harvested carbon. Potato farmers harvested 23,000 tons of carbon while sweet potato farmers harvested 2,300 tons.

Hay and Silage

Hay and silage are an important food source for Texas livestock. Hay production occurs statewide and is relatively uniform except for elevated levels in the northeast central plains (Figure 31). Of all harvested crops 25% is from combined hay and silage crops (7.2 million tons). Hopkins County in northeast Texas harvested the greatest amount of hay and silage (182,000 tons of carbon), whilst the per county average was 29,000 tons.

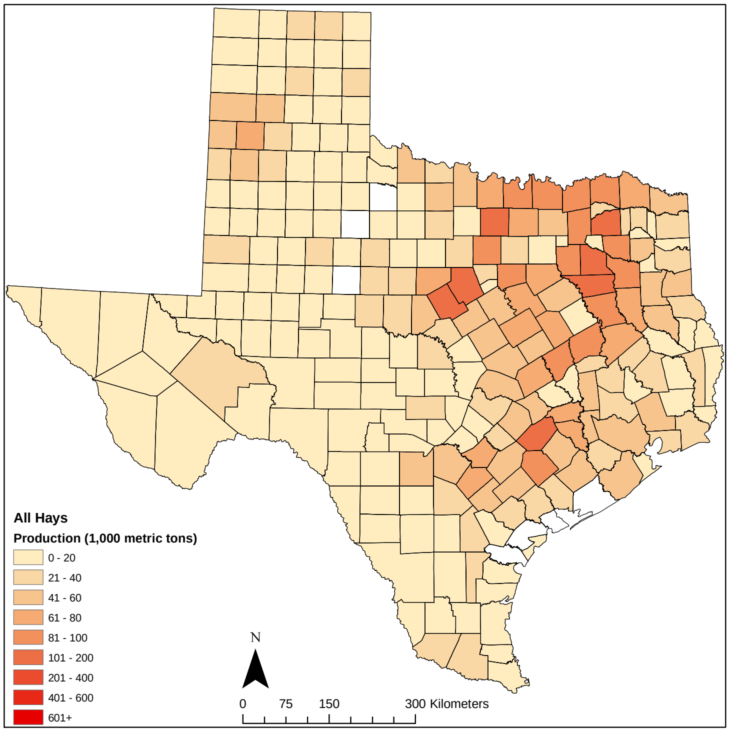


Figure 31: Average harvested carbon from all hay and silage between 2000 and 2005.

Corn for Silage

Corn grown for silage, to be used as livestock feed, is grown throughout the state with the exception of the Gulf Coast Plains and the Rolling Plains northwest of Fort Worth (Figure 32). Particularly high levels of production were found in north central Texas, the lower Rio Grande Valley, and Brewster County around Big Bend. The counties in the Panhandle harvested 134,000 of the 415,000 tons of carbon from corn for silage. The per county average was 1,900 tons.

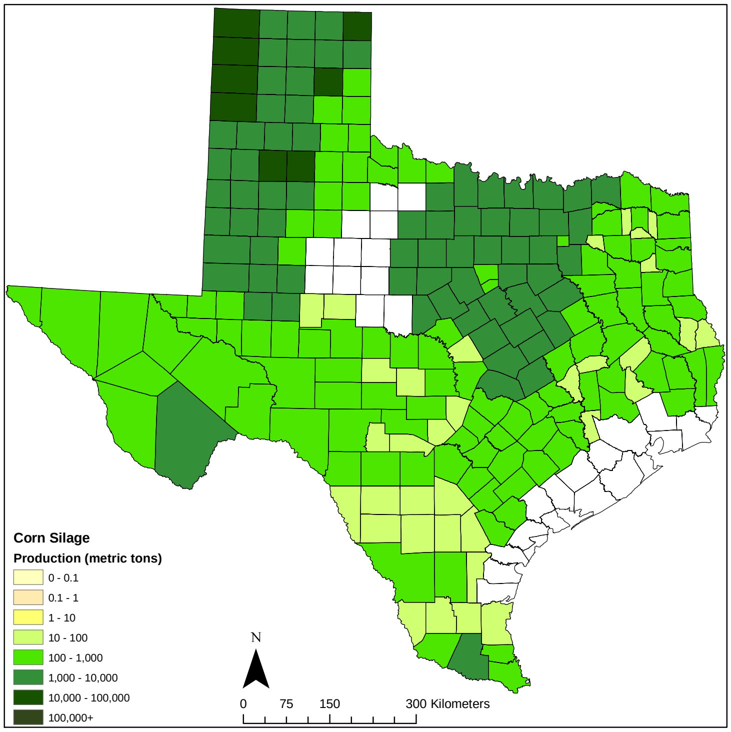


Figure 32: Average harvested carbon from corn for silage between 2000 and 2005.

Hay

Most carbon harvested in the hay and silage category comes from hay harvests. Of the 7.2 million tons of carbon harvested in the broad Hay and Silage category, hay represents the greatest percentage (89% or 6.4 million tons). It is no surprise then that the top producing county overall, Hopkins, is also the top hay producing county (162,000 tons). The average amount of carbon harvested by counties growing this crop is 34,000 tons. Spatially, hay is not limited by geographic region and is grown wherever possible (Figure 33).

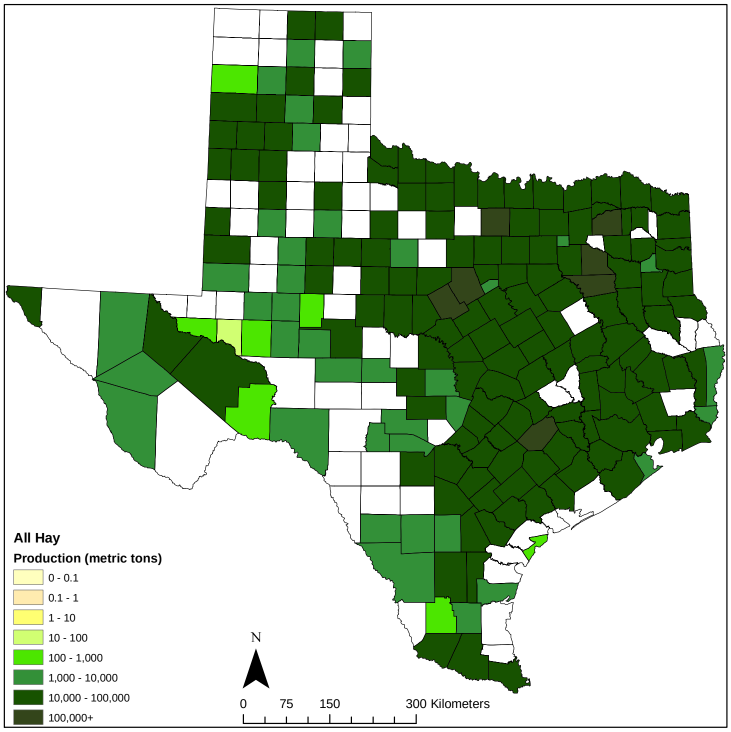


Figure 33: Average harvested carbon from hay between 2000 and 2005.

Haylage

The carbon harvested for haylage, or silage made from hay, follows a similar spatial pattern (Figure 34). The major difference is relative amount with hay being much greater. Statewide, 140,000 tons of carbon was harvested from haylage. Erath County, south of Fort Worth, harvested the most (21,000 tons) and Hopkins County, in northeastern Texas, the second most at 13,000 tons. The county average was 877 tons.

Interestingly there is no apparent pattern to haylage efficiency (NPP) (Figure 35). NPP from hay on the other hand exhibits a southeast to northwest trend as well as strong productivity in west Texas (Figure 36).

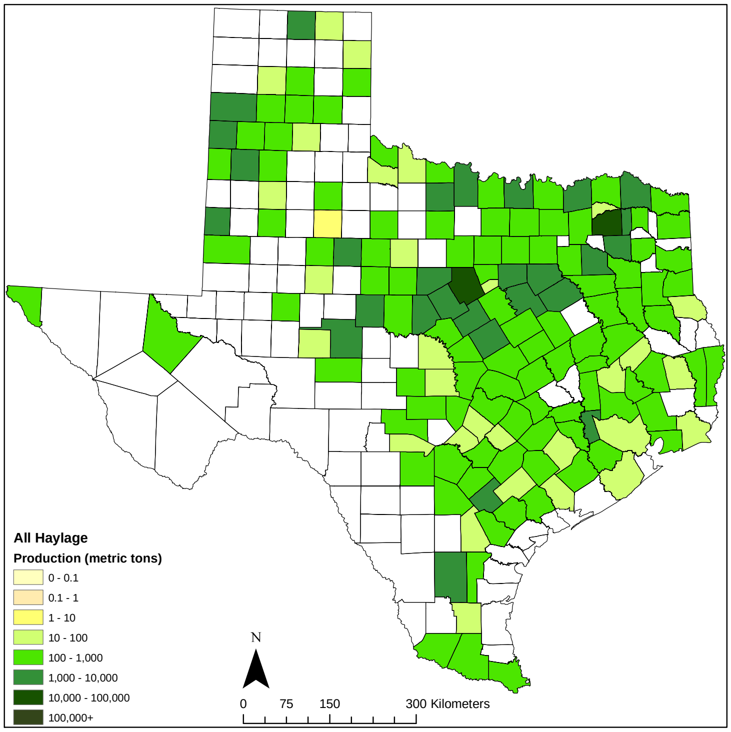


Figure 34: Average harvested carbon from haylage between 2000 and 2005.

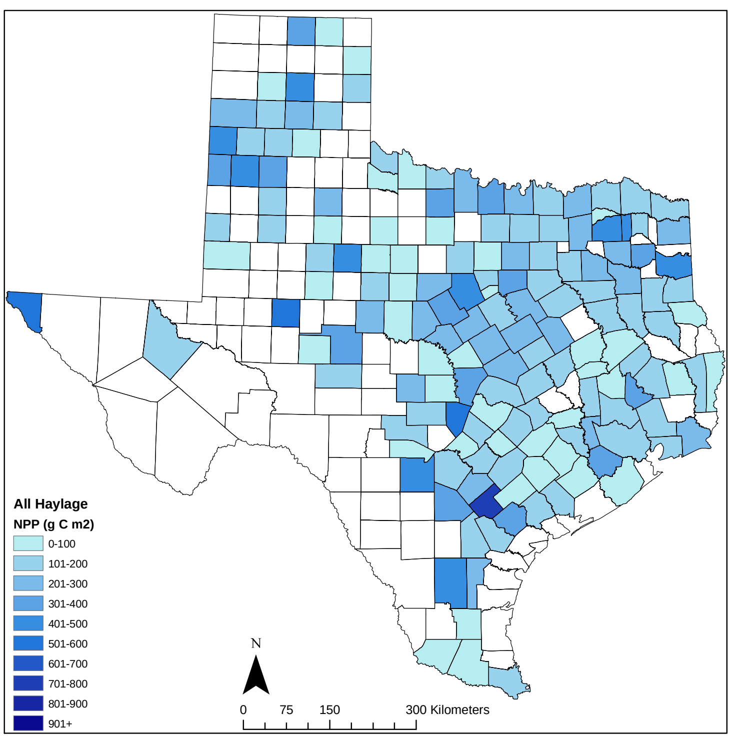


Figure 35: Average NPP of haylage between 2000 and 2005.

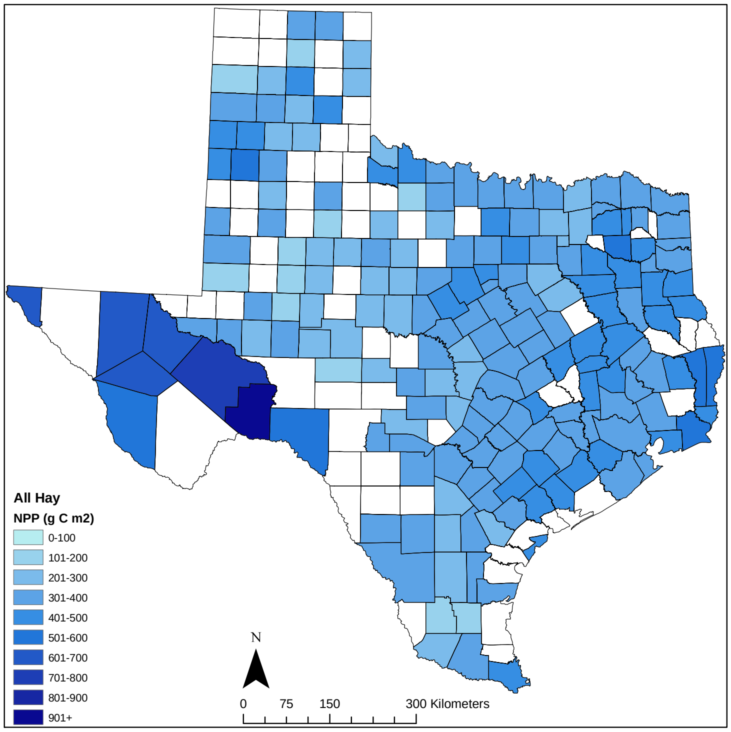


Figure 36: Average NPP of hay between 2000 and 2005.

Sorghum for Silage

Sorghum grown for silage has a scattered distribution extending from the Rio Grande Valley northwards along the I35 corridor and in the Panhandle (Figure 37). In total 182,000 tons of carbon was harvested from sorghum used for silage; this averages out to 2,300 tons per county. Castro County, in the Panhandle, harvested the greatest amount of carbon (20,000 tons) for sorghum silage.

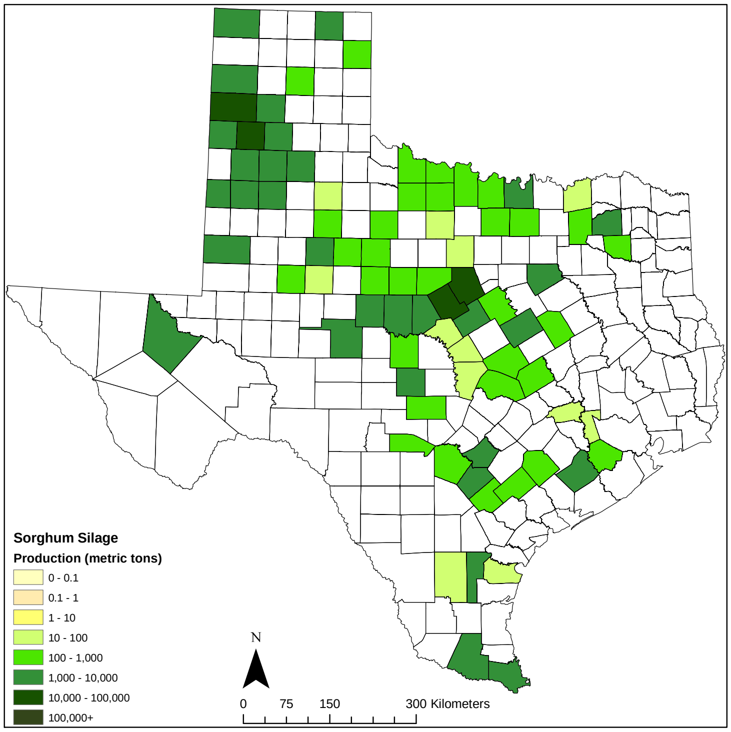


Figure 37: Average harvested carbon from sorghum for silage between 2000 and 2005.

Other Hay Crops

Other crops used for fodder and silage were not presented in detail because either spatial coverage is lacking or the amount of carbon harvested was very low. Details on these crops can be found in Appendix C. Bahia grass seed is grown in east Texas where it contributes 109 tons of carbon to statewide harvests. Other seeds (a USDA category for miscellaneous seed crops) contributed 64 tons of carbon from two counties in the Panhandle, and 1.7 tons of carbon was harvested from rye grass.

Vegetables

Compared to grain, hay, and 'other field crops', vegetable crops harvest relatively low amounts of carbon in Texas (Figure 38). Only 47,000 tons of carbon is harvested from vegetables statewide or 0.16% of all harvested carbon. The average carbon harvest for vegetables per county was only 324 tons. Hood County, south of Fort Worth, harvested the least (26kg) and Hidalgo, in the Rio Grande Valley, the most (17,000 tons).

Distribution of vegetables does not correlate with the natural southeast to northwest NPP trend. Technological intervention (intensive management and irrigation practices) are much more influential on vegetable production than environmental conditions. There is therefore a departure from the natural spatial pattern in favor of an irrigation driven one.

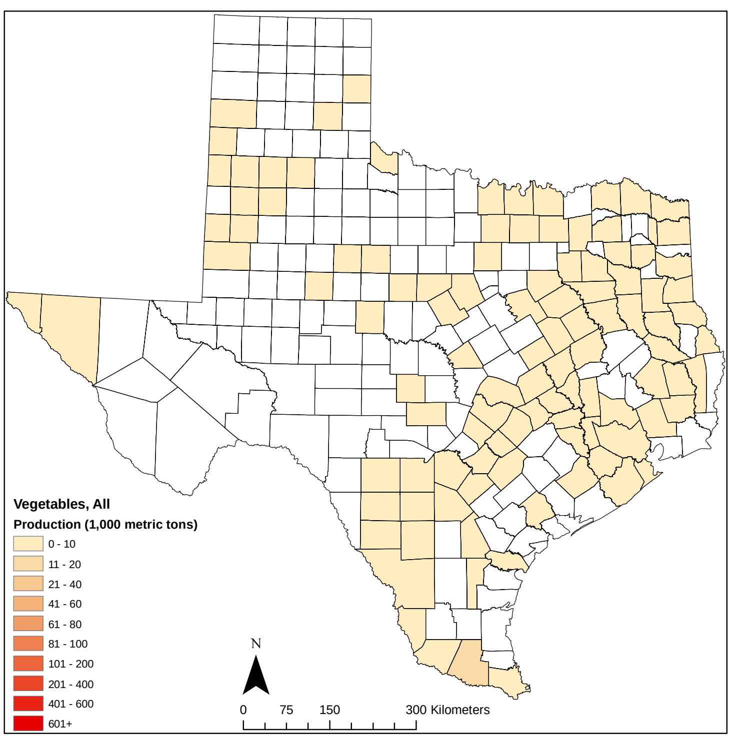


Figure 38: Average harvested carbon from all vegetables between 2000 and 2005.

Cantaloupe

Cantaloupe is the least productive crop in this study. Only 21 tons of carbon were harvested from cantaloupe in Texas. This averages out at 270kg per county growing cantaloupe. Hidalgo harvested the greatest amount at 9 tons, while seven counties (Bandera, Brazos, Harrison, Jefferson, Rains, and Rusk) each only harvested 3kg. Cantaloupe production does have a uniform distribution across the state (Figure 39).

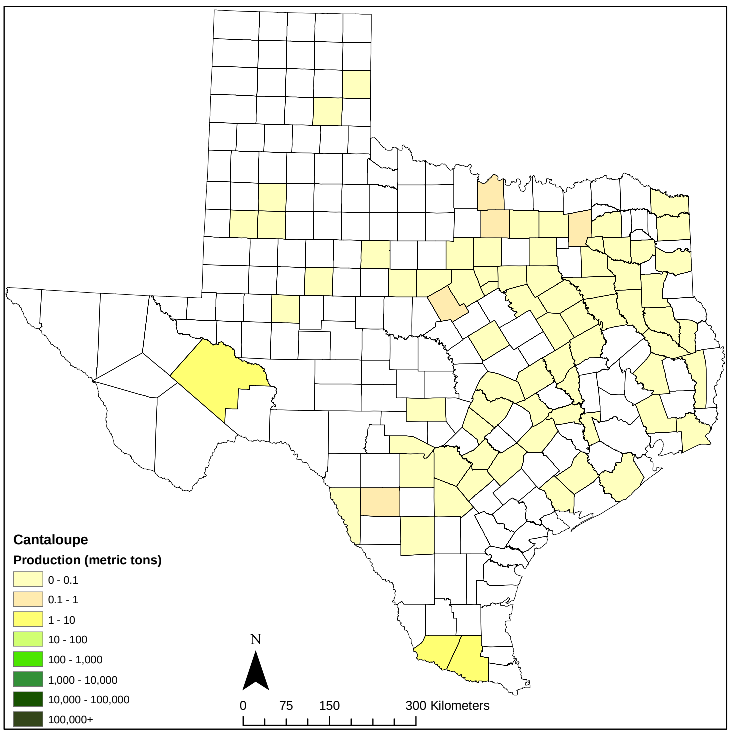


Figure 39: Average harvested carbon from cantaloupe between 2000 and 2005.

Chili Pepper

Hudspeth County near El Paso, Hidalgo in the Rio Grande Valley, and Medina near San Antonio produced the greatest amounts of carbon from their chili pepper crops (Figure 40). Respectively they harvested 1,200, 137, and 10 tons of carbon. Collectively this is 96% of all carbon harvested from chili peppers in Texas.

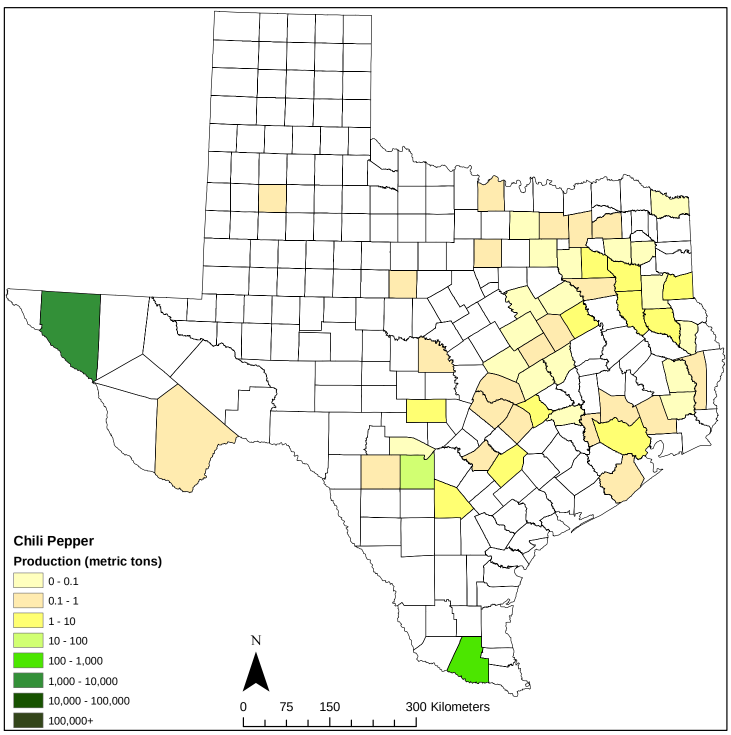


Figure 40: Average harvested carbon from chili pepper between 2000 and 2005.

Onions

Onions are mainly grown in the Rio Grande Valley (Starr, Hidalgo, Willacy and Cameron counties), south of San Antonio (Uvalde, Medina, Frio and Zavala counties), adjacent to Houston (Brazoria and Harris counties) and in El Paso County (Figure 41).

Across Texas 11,000 tons of carbon is harvested through onions. The county average was 188 tons, with Hidalgo representing over half this with 7,700 tons.

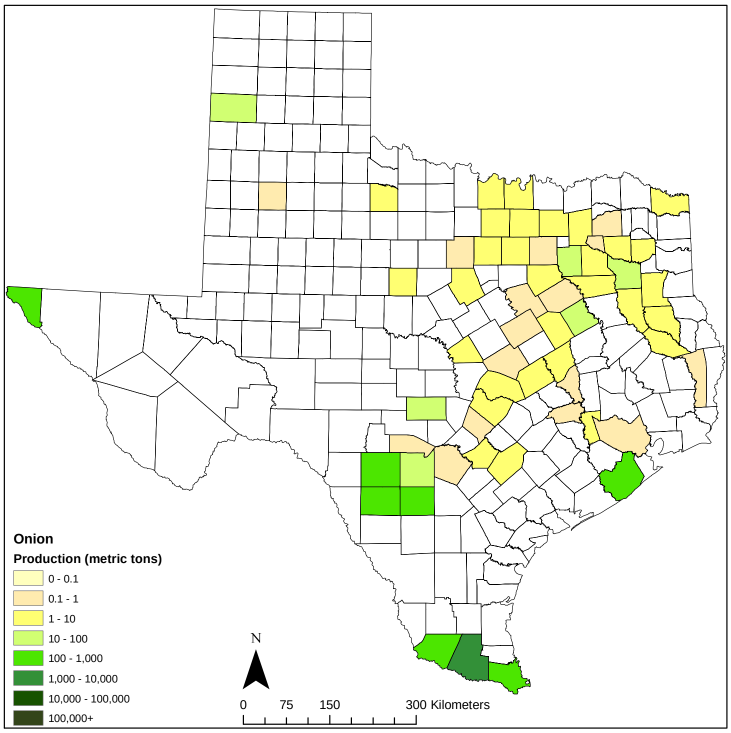


Figure 41: Average harvested carbon from onion between 2000 and 2005.

Sweet Corn

Of the 9,400 tons of carbon harvested from sweet corn most is from Hale County in the Panhandle and Hidalgo County in the Rio Grande Valley, 6,300 and 1,100 tons respectively. The remaining counties fall below the average of 224 tons (Figure 42). Spatial patterns are vague but seem to relate to either key agricultural zones (e.g. Hidalgo and Cameron Counties in the Rio Grande Valley) or adjacent to urban areas

(Hale and Lubbock Counties for Lubbock, Bexar and Medina for San Antonio, Harris for Houston, and Cooke and Grayson for Dallas/Fort Worth).

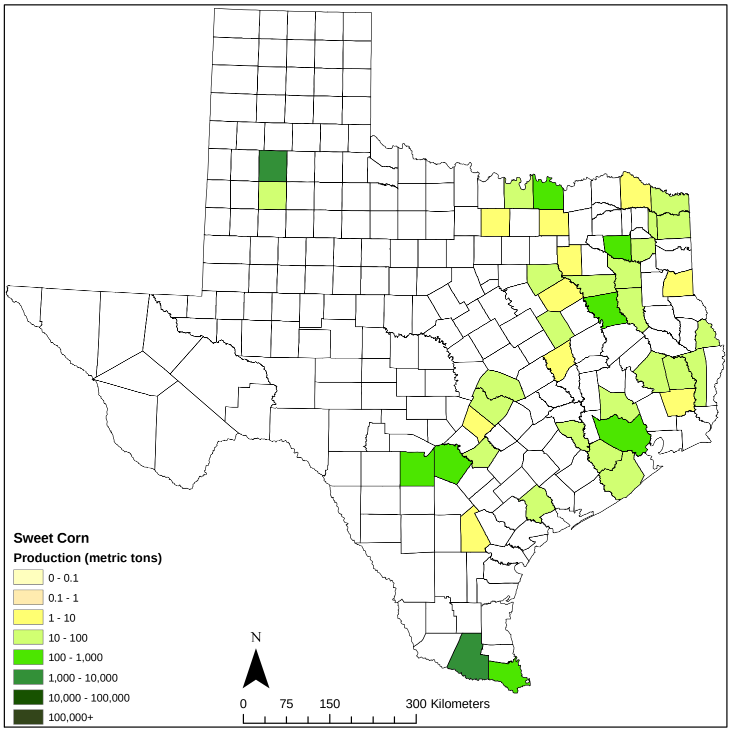


Figure 42: Average harvested carbon from sweet corn between 2000 and 2005.

Tomato

As with many other vegetable crops Hidalgo again is the dominant county. It harvests 122 tons of the statewide total 454 tons. Van Zandt in northeast Texas, Gillespie in central Texas, and Brazoria on the Gulf Coast Plains are the next three in terms of production. Together these counties harvest 44% of all carbon from tomatoes. Again, as with other vegetable crops, spatial patterns are driven more by market centers and urban areas than environmental conditions (Figure 43).

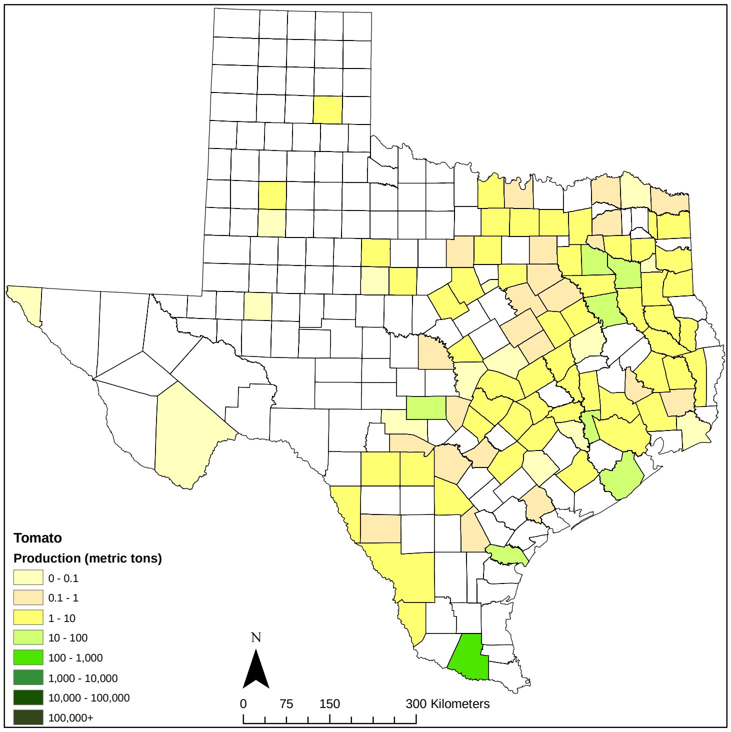


Figure 43: Average harvested carbon from tomato between 2000 and 2005.

Watermelon

Watermelon cultivation is dispersed across the state except for west Texas (Figure 44). Total carbon harvested from watermelons was 13,000 tons. The greatest amount was harvested in Hidalgo County with 4,000 tons of carbon. Montgomery and Travis counties both harvested the least at 409kg each.

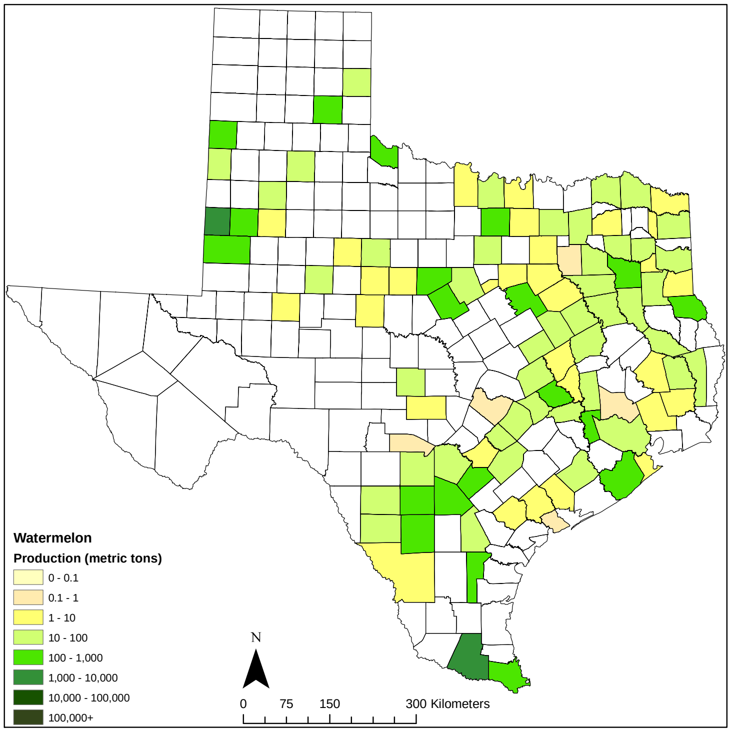


Figure 44: Average harvested carbon from watermelon between 2000 and 2005.

Other Vegetables

Other vegetables are not presented at depth here because their contribution to total harvested carbon was very small. Seven counties grew cabbage with a total of 487 tons of carbon harvested. Carrots produced 333 tons of carbon almost exclusively in Hidalgo County. Cucumbers contributed 2,000 tons of carbon; mostly in Hidalgo, Medina, and Hale counties. Pumpkin patches are limited to northern counties and produced approximately 1,000 tons of carbon. Spinach, which is limited to the Rio Grande Valley, produced about 1,000 tons of carbon. Snap beans are grown in east Texas and the northern Rio Grande Valley, contributing 433 tons of carbon. The distributions of harvested carbon and NPP for each of these crops can be found in Appendix C.

Fruit

General trends for all fruit crops tend to follow agricultural zones and urban centers rather than any natural spatial pattern. While spatial patterns for all fruits are not strong, there are unique patterns for specific fruits (Figure 45). Five percent (1.4 million tons) of total harvested carbon from all agricultural and timber industries is from fruit orchards (mainly citrus, grape, peach and pecan). Hidalgo County produces far more than any other county, and more than one third of the carbon harvested from fruit comes from this county alone. The average is 8,500 tons of carbon: Morris County harvests the least (8.9 tons) and Hidalgo the most (>500,000 tons).

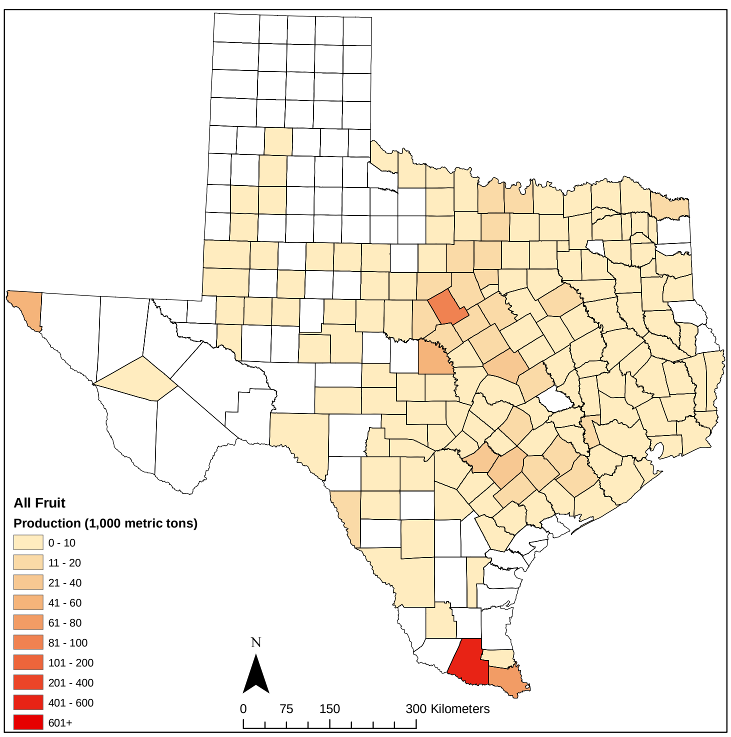


Figure 45: Average total carbon harvested from all fruit between 2000 and 2005.

Grape

There are several high production areas for grapes within the state (Figure 46). The two main areas are the Hill Country (Travis, Hays, Burnet, Blanco, San Saba, and Llano counties) and another in the Panhandle around Lubbock (Hale, Lubbock, Hockley, and Terry). Smaller but significant regions (Brazos Valley, northeast Texas, and Jeff Davis County in west Texas) appropriate moderate amounts of carbon through grape harvest. The harvest of grapes averages about 183 tons of carbon, with Lubbock County producing the most (1,900 tons). Total carbon harvested from grapes is 8,800 tons.

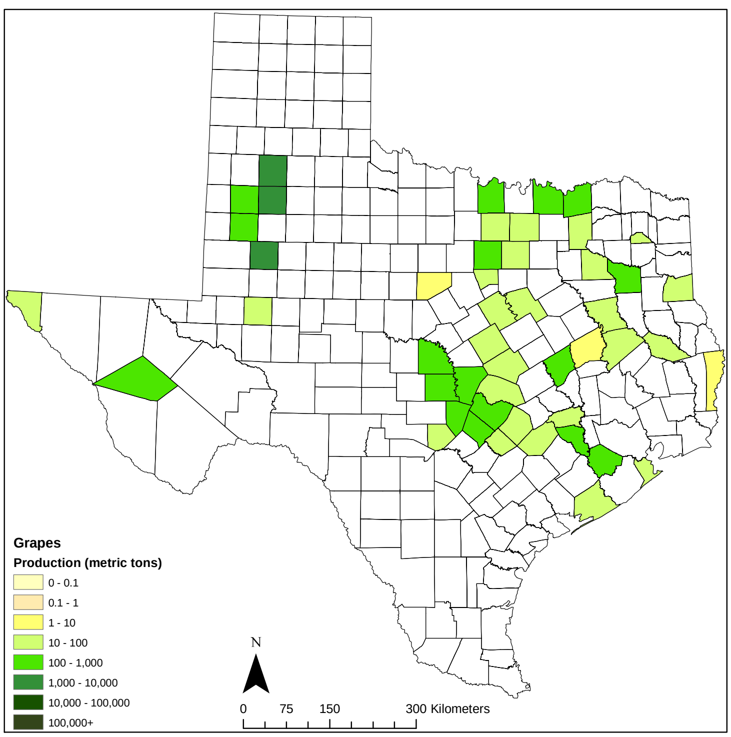


Figure 46: Average harvested carbon from grape between 2000 and 2005.

Peach

Peach orchards are concentrated in central to east Texas (Figure 47). These orchard crops are limited by temperature as well as pests (Smith and Anciso 2005). Although only 70% of the 4700 acres of peach orchards were harvested in 2002, this realized 11,800 tons of carbon. The county average was 161 tons: Newton County produced 3.4 tons while Gillespie County produced 3,700 tons from over a thousand acres under peach production.

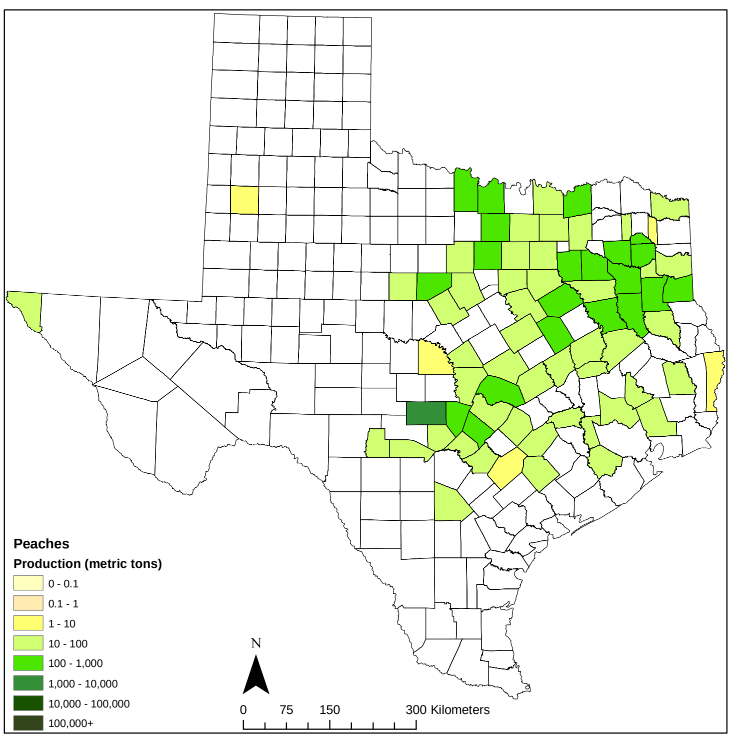


Figure 47: Average harvested carbon from peach between 2000 and 2005.

Pecan

The state fruit of Texas, the pecan, is widespread across Texas although there's little production in the Panhandle, west Texas and the lower Rio Grande Valley. The map of harvested carbon from pecans shows high values in a north-south arc from the Oklahoma-Texas border (Montague and Cooke counties) to the Gulf Coast Plains (Wharton County) (Figure 48). In commercial applications the orchards only produce a crop every other year, therefore in this analysis the commonly reported yield of 2000lbs per acre was divided in two (Aldred et al. 1997). This results in 816,000 tons of carbon harvested in pecans each year. The county average was 5,300 tons, with Comanche County having the greatest harvest (93,000 tons) and Cameron the least (6.5 tons).

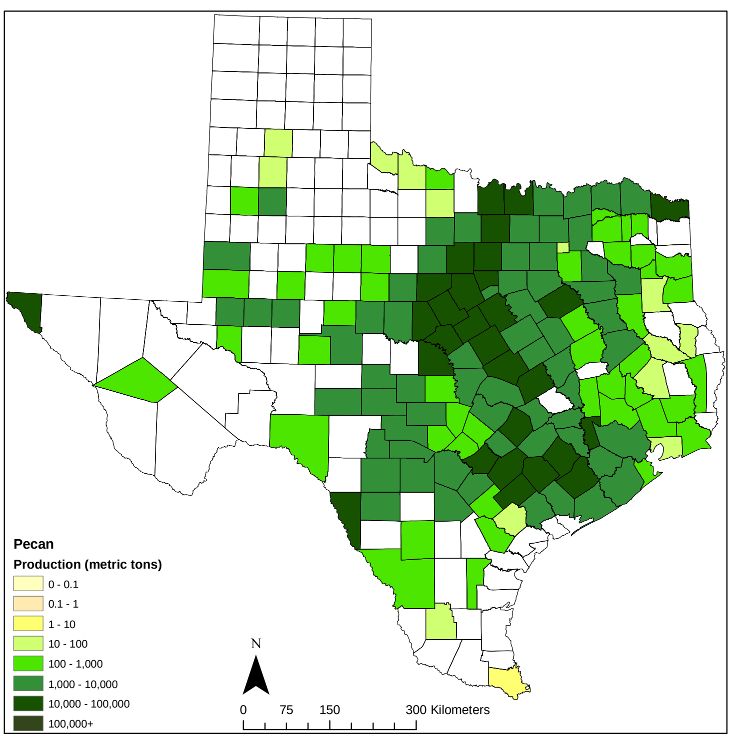


Figure 48: Average harvested carbon from pecan between 2000 and 2005.

Other Fruit

A significant amount of carbon was harvested from citrus. Production was spatially restricted to the lower Rio Grande Valley (Hidalgo, Cameron and Willacy counties) as well as Orange County in southeast Texas (Table 6). Maps of harvested carbon from citrus as well as NPP from all fruit crops can be found in Appendix C.

Table 6: Counties harvesting citrus between 2000 and 2005. Excerpted from Appendix B.

County	Production (1,000 tons)
Orange	0.08
Hidalgo	503.78
Willacy	3.64
Cameron	62.06
Total	570

CHAPTER V

DISCUSSION

To contextualize HANPP in the state it is important to compare results from Texas to those from research elsewhere. MODIS-derived products therefore, harvested NPP, carbon production, and finally HANPP are compared to the literature. Having validated the results the discussion goes on to identify potential issues in using these data, and research design. Finally the discussion ponders what these results mean for the sustainability of agricultural and timber sectors in Texas.

Validation

MODIS-NPP Estimate

The spatial distribution of NPP estimated from MODIS data in Texas fits well with the anticipated patterns discussed in the literature (Hicke et al. 2002; Lauenroth, Burke, and Paruelo 2000). NPP was highest in the southeast (where values reached as high as 1840 g C m^{-2} in Brazoria County), and lowest in the west (where values fell to zero) (Figure 7). This distribution confirms that moisture availability is the strongest overall environmental influence on NPP in Texas (Lauenroth, Burke, and Paruelo 2000).

Harvested NPP Estimates

Estimates of harvested NPP also compare well with the models of (Hicke, Lobell, and Asner 2004; Lobell et al. 2002; Prince et al. 2001) for similar, contemporary U.S.

agricultural systems. In particular, C4 plants such as corn have the highest efficiency – NPP – in Texas (Prince et al. 2001). The results from the data presented here support this point, as carbon harvested for grain corn was both prolific across the state and among the most efficient (highest NPP).

While the harvested NPP estimates for Texas compare well to other estimates this research also illustrates some of the difficulties in interpreting spatially-explicit harvested NPP. NPP for harvested crop totals (all timber, all grain, all hay, etc) can be deceptively low, because all crops are divided by the total area of the county, rather than by the specific area under agriculture. It would be more accurate to divide total carbon production estimates by the exact area cropped but definitions in USDA crop data make identification of the exact area problematic. This is because of intercropping and multiple growing seasons within a year. Sugarcane, for example, is harvested a number of times each year as well as its entire life cycle. This temporal mismatch biases assessments of total area and quantity of carbon harvested per year. For fruits and vegetables USDA does not report either an amount produced or a yield, only acres planted and acres harvested. Therefore to compute harvested NPP a regionally-specific yield had to be applied to each fruit or vegetable, but as these generic yields are uniform across the state when used to compute NPP values, these are also uniform across the state. Timber harvest data also complicated the traditional methods of measuring harvested NPP. While calculations of harvested NPP assume an entire discrete unit of area (m^2) is harvested, some modern forestry practices employed in Texas use selective logging (Pulkki 1997; Xu and Carraway 2005), in which only a portion of the aerial unit measured is harvested. With the complete harvest of a monoculture, such as a corn field, NPP calculations will give an accurate measure of efficiency, but if incomplete, as with selective logging, the measure may be much more conservative. Timber also does not conform to the same temporal scale as the majority of other agricultural crops. That is, its life-cycle is not contained within the same temporal unit (one year) as the NPP measurement. Comparing actual carbon produced (harvested) to the quantity of carbon present (MODIS) attempts to compensate for this short coming. Yet, because MODIS represents what carbon was sequestered for that time period the amount of carbon already sequestered in the system is unknown. Therefore an already present amount of carbon remains unknown.

This research shows, when viewed at the county resolution and over a large, geographically variable area such as Texas, conventional methods of estimating harvested NPP are inappropriate. For this reason carbon production was analyzed instead. Recall in Chapter III that harvested NPP is production divided by cropped area. Cropped area, for the reasons discussed above, is not well defined, but production, or the total amount of carbon in tons harvested per county, remains a sound measurement. Because total county production was used rather than efficiency, the MODIS data was converted into production as well (NPP * area).

Carbon Production Estimates

From the averaged six-year dataset, total carbon production (actual carbon estimated from MODIS data) in Texas was 268 million tons, with an average NPP of 400 g C m^{-2}. These estimates are well in line with other carbon studies of production in the agriculturally-dominated states in the U.S. (Hicke et al. 2002; Lobell et al. 2002; Prince et al. 2001; Turner 1987).

If total carbon production for individual counties is considered, carbon production ranges from 137,000 tons in Rockwell County to approximately 4 million tons in Webb County. However, differences in the size of counties, and therefore the potential area available for carbon production, distort county-level estimates immensely. When production is normalized by area, large counties in west Texas are clearly far less efficient than smaller eastern counties. This is due again to the increased moisture availability in east Texas. Considering these normalized values, the county with the highest carbon production was Brazoria (900 g C m^2) while the lowest was El Paso (123 g C m^2).

HANPP Estimates

The HANPP estimates for Texas are well within the range of other studies. The average HANPP for Texas - 13% - falls in the lower part of Rojstaczar et al.'s (2001) 10-55% range. It is also lower than the global estimates put forward by Imhoff et al. (2004), Vitousek et al. (1986), and Wright (1990:189). Haberl et al. (2001) estimated 50% of

NPP in Austria was harvested in agriculturally-dominanted regions. The main agricultural regions in Texas either exceed Haberl et al.'s estimate or are in the same range. For the state average, low values in west Texas (where economic opportunities in agriculture are drastically limited) reduce overall HANPP to bring the average below estimates from the literature (Table 7).

Table 7: HANPP literature.

Author	**HANPP**	**Extent**	**Spatially-explicit**
This research	13%	Texas	x
Haberl et al. (2001)	50%	Austria	
Haberl et al. (2007)	23.8%	Global	x
Imhoff et al. (2004)	31%	Global	x
Rojstaczer, Sterling and Moore (2001)	10-55%	Global	
Vitousek et al. (1986)	40%	Global	
Wright (1990)	20-30%	Global	

The spatial pattern of HANPP is similar to that of total carbon harvested with the highest rates of human appropriation being found in:

(i) the northern and western Panhandle;

(ii) El Paso County in west Texas;

(iii) the lower Rio Grande (Cameron, Hidalgo, Starr and Willacy counties);

(iv) along the Gulf Coastal Plain extending from Kleberg and Jim Wells counties eastward to the Louisiana state line;

(v) the timber counties in east and east-central Texas; and

(vi) northeast Texas along the Red River Valley.

For most Texas counties, human appropriation was less than 10% of NPP, but for ten counties more than 50% of available NPP was appropriated (see Table 3). In the latter counties, all of which are in the Panhandle, field and grain crops such as corn, wheat and sorghum dominate.

Islands of relatively high HANPP occur in regions of low to moderate HANPP. For example, Hidalgo, Willacy and Cameron counties in the lower Rio Grande Valley which produce the majority of the state's fruits and vegetables; El Paso County in west Texas which produces corn, cotton and hay; Hill County in north Texas which produces corn, hay, pecan, sorghum and wheat; and three counties of the Gulf Coastal Plain – Nueces, San Patricio, and Wharton counties dominated by corn, cotton, rice and sorghum. In total, 28.8 million tons of carbon were harvested from agriculture and timber in Texas. Two spatially competing trends are evident in these data. The first, and most obvious, is that apart from the counties with very high HANPP discussed above, high amounts of harvested carbon coincided with regions of naturally high NPP, i.e. along Gulf Coast Plains, and in east and east-central Texas. Crops such as hay, sorghum and wheat conform well to this pattern (i.e. a general southeast to northwest decline in NPP influenced by moisture availability). Counter to this is a trend driven by agricultural intensification facilitated by irrigation in the Panhandle and the lower Rio Grande Valley. Production of corn, soybeans, and peanuts follow this second pattern. For corn grown for grain, NPP_{corn} was greatest in the Panhandle and in the northwest. Wheeler County in the Panhandle had the highest value (1,341 g C m^{-2}) while Kleberg County on the Gulf Coast had the lowest (219 g C m^{-2}). Hicke et al. (2004) also noted these trends and argued that Texas was one of a handful of states where, although the total amount of land in agriculture had decreased in the past few decades, management practices have increased NPP in areas remaining under cultivation.

Whilst it would be easy to suggest that high NPP_{corn} in the Panhandle and west Texas is simply a result of irrigation (which is the case for most crops) that does not explain the low $NPP_{sorghum}$ or other crop values in the Panhandle. The high NPP_{corn} values in Texas, relative to other cereal crops, makes it one of the most NPP-efficient crops grown in Texas. This finding is in line with that of Prince et al. (2001, 1200) who reached the same conclusion explaining that as a C4 plant, it is simply more efficient than C3 crops such as sorghum.

There were also signs of the impact of elevated demand for agricultural produce from major urban areas on neighboring counties. Hudspeth County near El Paso, for example, harvests the greatest amount of carbon from chili pepper. This may also be driven by cultural demand. Another specialized crop that boosts carbon harvested around Austin, Dallas, Houston and San Antonio is the production of Christmas trees which are grown on farms in nearby counties.

Data and Methodological Issues

Raw Data

Conversion of masked pixels in the MODIS data was necessary before it could be incorporated into this study. Primarily this was because there were pixels in the raw data with no NPP values. It is fairly certain that pixels flagged as barren had an NPP value of zero (or close thereto). However, the methods employed in this research to account for pixels flagged urban may have lead to conservative estimates of actual NPP. As discussed in Chapter III, pixels adjacent to urban pixels, but identified as belonging to the same urban area, were averaged and that average assigned to all the flagged (missing data) pixels. Moreover, because the urban masks in the MODIS dataset do not accurately reflect the actual urban extent (nor do they represent the densest areas of urbanization) there was strong evidence supporting using adjacent pixels, within the same urban extent, to calculate values for the masked pixels. Unfortunately in small urban areas, such as those south and west of the Dallas/Fort Worth metroplex, results suggest actual NPP could be higher than the extrapolated NPP value. Urban areas in this region salt and pepper the counties, covering a large amount of the area. Furthermore agricultural results indicate high production in the area of wheat and cotton. The conservative estimate from the MODIS, estimated actual NPP, and high agricultural production could be skewing HANPP in this region. Without the MODIS values, or an alternative method to calculate actual NPP in these urban areas, the full extent of such a bias is unknown but estimated to be minimal considering the entire state.

The overall low HANPP values for Texas may partly be influenced by USDA reporting methods. Hicke et al. (2004) investigated which U.S. states were missing data from the USDA database. Texas was one of a handful of states where missing per-county data was common for their study period. An evaluation of the frequency of missing data in this study showed that roughly one third of the counties were missing half the six years of data for a given crop, but the majority of these were the lowest-producing counties for that crop. Records for the highest producing counties for a given crop were always nearly complete or complete. In this study the annual crop data for each crop were averaged together. If a county was missing data for specific years those years were left out of the crop average for that county.

For some other crops the data were not used because their volumes were insignificant in either yield or acres harvested. They were deemed minor contributors to Texas agriculture and therefore to statewide HANPP. These crops include some berries, herbs and a few minor vegetables (e.g. blackberries and asparagus). This was also a practical decision as these crops lent little to the overall Texas agricultural industry in terms of carbon harvested therefore the effort to convert USDA census data to carbon appeared moot. Similarly, these crops were usually geographically isolated within the state lending little explanatory power to changes in NPP across the state. In many instances these data were also plagued by missing or incomplete records. A threshold was used in the study. If the overall contribution to NPP of a given crop was < 10 metric tons for all counties from the six-year averaged dataset the crop was ignored.

A further issue leading to the conservative bias in the estimates was censorship within the USDA data. For example, if only one farm grows a particular crop within a county all that crop's data for the county is not reported. Regardless of the size and level of production of an individual farm, the data is censored to preserve that farmer's anonymity. As a result there is an unquantifiable amount of crop data missing in the USDA database. An analysis of regional data reported by the USDA compared to the county-level might elicit a better idea of how much is censored, but because of the spatial resolution of this research it would not have helped recover the censored data. Both the King Range, covering four counties in the Rio Grande Valley, and the 46's Range west of Fort Worth represent two major agricultural operations that, because they are single organizations, their statistics, though significant, are censored.

There are some uncertainties in the area under cultivation for a few crops. These errors are introduced because of inter-cropping and multiple growing seasons within a calendar year. Due to USDA's reporting methods it is unclear which crops are inter-cropped together or which have multiple harvests per year, making an accurate estimate of NPP for these crops difficult. Fruits and vegetables are only reported in acres cropped, rather than yields as with other crops. As a result the area harvested is known but the amount harvested is unknown. These uncertainties compromise the accuracy of harvested NPP for some crops.

Regardless of the issues inherent in the USDA agriculture census data, it is still the most accurate and reliable data source. The length and scope of the census are unparalleled at this spatial resolution. Because of this, and the federal backing of data collection and processing, there is still great confidence in the results from the agricultural data (Hicke, Lobell, and Asner 2004; Prince et al. 2001; Turner 1987).

The Texas Forest Service data elicits a few uncertainties in the timber growing counties. First is that the data are only reported for the 43 major timber-producing counties of east Texas. Minor logging operations elsewhere in the state, which could still contribute significant amounts of harvested carbon, are not reported.

The temporal differences between an annual crop and timber production in NPP calculations is well documented (Haberl et al. 2001; Kicklighter et al. 1999; Rojstaczer, Sterling, and Moore 2001; Turner 1987). The same issues arise in this study. First, logging practices in Texas do not conform to the total number of acres harvested for annual crops. In the latter, NPP assumes total production per unit area, but in logging its only a portion of a unit's area in any given year. This is yet another argument for basing the study on harvested production per county rather than NPP per county. Furthermore, traditional measures of harvested NPP assume crop production occurs within one year. For timber this is far from the case. MODIS data reports NPP for the year, but fails to account for the accumulation of carbon over decades. This means that for timber the HANPP comparison is between newly sequestered carbon and harvested carbon, while for annual crops it is between total accumulated carbon and harvested carbon. The difference means that for forests there is no notion of how much actual stored carbon is present using this method, only what is added or taken away in a given year.

Finally the Texas Forest Service reports timber harvest per county while they report harvest residues (used to calculate the Harvest Index) as a total for the whole 43 county region. Because the value is regional and not county specific there will be some variations in harvested carbon that is not accounted for. Again these methods sought to lean to the conservative side and therefore might underestimate HANPP slightly in the timber industry.

Conversions

Despite the fact that NPP and HANPP estimates are in line with those of other researchers, errors and uncertainties still exist. Most important are published conversion values for harvest indices (HI), above-to-below ground plant ratios (*fAG*), and moisture content (MC) at fairly refined scales. Harvest indices are known to vary with harvesting methods and these evolve over time (Turner 1987). In Texas, where agricultural experimentation is a high priority, the indices used may not be valid for long. Furthermore HI for any given crop may not be consistent across the study area as both different technologies and labor inputs can influence harvest methods. The difficulty in finding published values for the wide variety of crops grown in Texas, for both the correct temporal period as well as geographic location, may have influenced the results.

The ratio of above-to-below ground plant mass (*fAG*) is poorly understood and under-researched (Gill et al. 2002; Jackson, Mooney, and Schulze 1997). Many of the *fAG* values are interpreted liberally in the literature (Hicke, Lobell, and Asner 2004; Lobell et al. 2002). Fortunately Prince et al. (2001) reveal that variations in *fAG* are less influential in converting crop production to carbon than the harvest indices.

Variations between crop varieties could potentially lead to variability in moisture content. Unfortunately USDA publishes little on different crop varieties. In this study corn was broken down into that for grain and silage, and sweet corn; and cotton into

American Pima and American Upland. Moisture contents were assumed constant for corn and cotton respectively as there was no data to the contrary.

Sherman County in the Panhandle exemplifies how errors propagate through a dataset. A strict interpretation of the results indicate that this county harvests 7,400 tons more carbon than is actually available (101.27% HANPP). Obviously it is not possible to harvest more than is present. There are a number of possible explanations for this. First, methods to collect and report agricultural census data by USDA (particularly rounding up errors) could have led to overestimates of the areas harvested for each crop. More likely though is variability in the harvest indices applied to each crop grown in Sherman County. Prince et al. (2001) discuss how variability of the harvest index can account for fluctuations in results up to 10%; 7,400 extra tons could easily be explained by harvest indices uncertainties as it is within this 10% margin.

Land-Cover Change

This study only calculates human appropriation for crop and timber harvests. This offers a somewhat limited scope in terms of sustainability research compared to some other HANPP studies (Bradford, Lauenroth, and Burke 2005; Haberl et al. 2001; Haberl, Schulz et al. 2004). HANPP studies often include appropriation through land-cover change which will alter vegetated surfaces. Human appropriation can both reduce potential NPP due to urban expansion and infrastructure development or increase NPP through agricultural intensification and management. HANPP due to land-cover transformations were not directly accounted for in this research for two reasons.

First, because the temporal scale of this research covered only six years – 2000 to 2005 – significant changes in land-cover are assumed to have relatively little impact. At a national to global scale rapid land-cover change can have a greater impact, but because Texas is well-developed, radical changes in land-cover are unlikely during this period.

Second, the MODIS NPP product records actual NPP and therefore inherently includes the effects of land-cover change. As land-cover change impacts NPP the MODIS sensor indiscriminately records the change although remote sensing cannot distinguish between what caused the change. Other studies use calculated estimates of vegetation composition before human impact. They use the difference between actual NPP and their estimated pre-human impact NPP to calculate the extent of land-cover change. Pre-human NPP is used as a surrogate for potential NPP. This is of course only a best guess and has little impact on the changes occurring post-human impact.

Given the expansion of urban areas in many parts of Texas, land-cover change would be an important consideration in studies which incorporate a long temporal dimension. For such a study keeping the various datasets separate rather than averaging (i.e. MODIS and corresponding crop statistics) would enable a more complete integration of land-cover change. Furthermore, and as discussed above, conversion variables like HI have been shown to change over time. The goal of this study though was to calculate the spatial pattern of HANPP rather than temporal change.

Sustainability

Using HANPP as a measure of sustainability provides interesting insights about the state of agriculture and timber in Texas. NPP follows two spatially-distinct trends: a natural pattern influenced strongly by moisture availability, and an anthropomorphically-induced pattern. The abundance of carbon in areas where NPP is naturally high is relatively untapped and therefore these regions (i.e. east Texas, east-central Texas and along the Gulf Coast) have a relatively low HANPP. These areas are able to support current human appropriation or even support slight increases in appropriation while remaining sustainable in terms of carbon. Large-scale, high-intensity cultivation in regions such as the Panhandle and lower Rio Grande Valley artificially increase NPP with the use of irrigations, fertilizers and other agrochemicals, and agro-technology like high-yield crop variations. In terms of ecological sustainability, measured through species diversity, carbon in these areas can be viewed as unsustainable. If viewed in terms of agricultural efficiency these areas are extremely efficient and sustainable. But considering the amounts of fertilizers, chemicals, and supplemental water necessary to sustain industry in these regions, agriculture in these regions seem ever more tenuous.

Agricultural efficiency supports the idea that a higher percentage of human appropriation equals greater efficiencies. This efficiency can be translated into economic sustainability. This is why, although unsustainable from an ecologic point of view, from agriculture's economic perspective the lower Rio Grande Valley and the Panhandle are very efficient and therefore economically sustainable. Other regions such as the Red River Valley and the Gulf Coast Prairies exhibit the opposite; increased ecological sustainability and decreased economic sustainability as HANPP is only 10-20%.

Where NPP is greatest (i.e. in the Pineywoods of east Texas and on the Gulf Coast Plains) human appropriation is around 20%. The forests of east Texas have the ability to sequester significant amounts of carbon, and managing timber extraction from these forests has restrained HANPP and allowed large amounts of carbon to be sequestered. This makes plans by Temple Inland (Babineck 2007) to sell the majority of its stake in east Texas worrisome unless the scattered conservation units in the region can be expanded or alternatively other timber companies buy these lands and manage them as conservatively as they are at present. The practice of clear felling for a quick profit, or the development of forested land into urban land could quickly diminish sustainability of the region.

The Gulf Coast Plain, due to its abundant moisture, has naturally high rates of NPP. While harvests of corn, cotton, hay, and sorghum are high in this region, the abundance of naturally sequestered carbon compensates and keep HANPP low. Based on the

HANPP results from this research it could be concluded that in terms of carbon and ecological sustainability, the Gulf Coast Plains are currently sustainable.

Urban expansion along Interstate-35 has led to moderate appropriation in the range of 10-30% of carbon from harvest. Urban growth coupled with corn, hay and sorghum with irrigation, and pecan orchards dominate this region. While sustainable in terms of carbon, competition for land along the corridor is growing rapidly. Urban expansion will continue to convert vegetative land-covers for urban land-covers, reducing available carbon. Plans for the Trans Texas Corridor are well under way (Palacios 2005). This, coupled with urban growth will appropriate greater amounts of NPP and significantly increase HANPP through land-cover change. Although appropriation through land-cover change was not modeled explicitly in this research, its effects are assumed in the MODIS data representing actual NPP.

The I-35 region, although drier and warmer than Haberl's Austrian studies (Haberl 1997; Haberl, Erb, and Krausmann 2007; Haberl, Fischer-Kowalski et al. 2004; Krausmann and Haberl 2002), compares well in terms of population density, diversity of agricultural practices and HANPP. The comparable values of HANPP along the Texas I-35 corridor (20-30%) and in Austria (23.8%) support the idea that the economic suitability for agricultural practices plays a significant role in HANPP.

In terms of sustainability, while naturally high regions of NPP can better support agricultural sustainability, they do not necessarily determine where humans will appropriate. The key examples of this are the lower Rio Grande Valley, and the Texas Panhandle. Agricultural intensification, particularly through the increased use of fertilizers, pesticides, and most importantly, irrigation, have led to large-scale agricultural change and increased harvests in the lower Rio Grande Valley and the Panhandle (Tiefenbacher 2001). Hidalgo, Willacy, and Cameron Counties of the lower Rio Grande Valley are the state's major fruit and vegetable producers. As the chief economic industry in these counties the priority is given to the crops. Advances in irrigation technology have allowed intensification through increased efficiency. Irrigation and intense management coupled with only moderate natural NPP have lead to 30% HANPP and greater.

The Texas Panhandle counties offer even more extreme examples. The ten counties appropriating the most carbon in Texas are all in the Panhandle. All ten appropriate greater than 50% of available carbon, which is well above global averages and at the upper end of Rojstaczer, Sterling, and Moore's (2001) findings. Landscapes in these counties have become cereal monocultures and because maintaining the high harvest volumes of these crops requires equally high supplemental inputs and irrigation, overall agricultural sustainability at current levels is questionable. In terms of carbon, some of these counties (those with HANPP above 90%) are appropriating almost all available carbon. This shows how technology facilitates extreme efficiency in human appropriation, but between nearly complete appropriation and the transformation of the local ecosystems to vast monocultures, sustainability in terms of other indices also appears controversial. For example, an increase in HANPP has been shown to decrease biodiversity; itself an indicator of ecosystem health and stability (Haberl 1997; Milesi et al. 2003; Vitousek et al. 1997). Furthermore the intensification in agriculture leads to increased consumption of water, fertilizers and pesticides. Although technology has facilitated such high agricultural efficiencies, if technology does not continue advancing sustainability surely would not be possible. In the Panhandle, water in particular is limited and already deeply contested (Dugan, McGrath, and Zelt 1994; Griffin and Characklis 2002). The extensive use of irrigation has even been shown to negatively impact precipitation in the Panhandle (Moore and Rojstaczer 2002). Issues of sustainability due to fertilizer and pesticides contaminating water supplies in this region has also been considered by Mapp (1994).

Taken as a whole however, HANPP in Texas is on par if not below other estimates of HANPP. This may appear to bode well for overall agricultural sustainability in Texas, but removing lightly used lands in west Texas from the analysis - due to their arid, marginal status – increases overall HANPP and it is then on par with other estimates. Urban growth will continue to increase HANPP and therefore jeopardize sustainability. Growth will come in the form of land-cover change rather than harvest (Palacios 2005). Technological advancements are predicted to decrease the area under agriculture, but intensify the most economically productive areas (Prince et al. 2001). Therefore the spatial extent of agriculture's impact on HANPP will decrease but it will intensify in the remaining areas. Advances in biotechnology will facilitate increased production on marginal lands, and genetic experimentation can create hardier, more productive crops. This is already becoming apparent in the lower Rio Grande Valley and especially in the Texas Panhandle.

CHAPTER VI

CONCLUSION

The estimates of HANPP from crop and timber harvests in Texas between 2000 and 2005, incorporating Prince et al.'s (2001) methods, MODIS-derived NPP and agricultural and timber statistics compare well with other studies (Hicke et al. 2002; Hicke, Lobell, and Asner 2004; Lobell et al. 2002). Moreover, despite the limitations discussed in Chapter V, the results yielded a powerful dataset with which to analyze the spatial distribution of HANPP. At the county-level, and for each crop, these methods have tremendous potential for understanding carbon dynamics, and it can be argued that at the national scale and at a county resolution it is one of a number of valuable ways of assessing sustainability in the rural economy. This study has shown that spatially-explicit maps of HANPP for the major crop and timber-producing regions of Texas can be produced and used to investigate the usefulness of HANPP as a technique for addressing spatial constraints on sustainability. Furthermore the extent of this study can be increased using the same, or similar, data across the entire U.S., and would still elicit consistent patterns of HANPP (a natural pattern bound by moisture and temperature as well as a human pattern encouraged by agricultural intensification, regional agricultural specializations, and market centers).

In terms of the sustainability of Texas agriculture, many counties in east and east-central Texas and on the Gulf Coastal Plain have relatively low HANPP values when compared to global estimates. Results support considering these counties sustainable in terms of carbon dynamics. Forestry management practices in east Texas mean the region is a major carbon sink and in carbon terms, the contemporary Texas forest industry can be considered sustainable. However, the situation in many Panhandle counties and, to a lesser extent, in the lower Rio Grande Valley indicates an unsustainable future for primary productivity in terms of carbon and, given the irrigation water and agrochemical inputs, it could be argued that farming activities in these regions are unsustainable in other ways as well.

Future Research

Below are further research possibilities including the integration of livestock production and outputs from aquaculture to provide a more robust assessment of agricultural sustainability. Assessments of HANPP using methods similar to those employed here could also explicitly account for land-cover change from urban and infrastructure expansion if a long time series of HANPP were being analyzed. Finally, the ultimate goal of these assessments of sustainability may require research into how fossil fuel use can be integrated, and energy from its consumption accounted for.

Secondary Production

Secondary agricultural production is from animal husbandry. Primary productivity, in the form of grains, feeds and supplements are fed to livestock before the animals are harvested and their carbon appropriated. In Texas the cattle, goat, and sheep industries are a major segment of the agricultural industry, cattle being almost 50% of the total agricultural industry in Texas (Texas Comptroller of Public Accounts 1996). Livestock consume a great majority of harvested grain (80% of U.S. grown corn and 50% of U.S. grown sorghum grain) as well as virtually all hay, silage and pasture (US Environmental Protection Agency 2008).

Other studies of HANPP have made estimates which include secondary production (Rojstaczer, Sterling, and Moore 2001). Aspatially, and at a national to global scale, Rojstaczer et al. prove including secondary production is feasible. But, at a sub-national scale and especially in spatially-explicit studies, many assumptions are required to calculate HANPP of secondary production. The main issue is that the carbon from primary productivity that will be used in secondary production is already accounted for when it is harvested. Consequently any primary productivity used for animal feed would be double counted; once when the grain was harvested and again when the animal was harvested. This would skew HANPP results significantly in states like Texas. Second, if livestock was included there would be no way the analysis would remain spatially-explicit as it would be erroneous to assume crops grown for animal feed are fed to the livestock solely within the same county. Feed is shipped to regional silos and distribution centers where it is then shipped elsewhere for consumption. This occurs within and across state boarders. Where feed comes from and where it goes are unknowns. Because the goals of this study were to evaluate the spatial patterns of HANPP in Texas, where NPP originates and where it is harvested is critical.

Accounting for livestock production would therefore negate the analysis of spatial patterns in HANPP.

In this study the majority of livestock inputs (grain and feed) are already accounted for. Pasture is the notable exception. Spatially-explicit estimates on the consumption of pasture through grazing for Texas are inconsistent and unreliable. This is partly because the physical conditions of a pasture, relying on moisture, change dramatically across the state. It is also unreliable because there are no regulatory agencies collecting uniform statistics on these pastures. Therefore pasture, a carbon source appropriated as livestock feed, was not included.

Currently there is no existing literature on the impact of secondary production on HANPP in a spatially-explicit form. To avoid the bias of double counting and the geographical origins of feed, such a study would have to focus solely on the appropriation of secondary production. This type of study would then complement, rather than integrate with, the conventional definitions of HANPP (human appropriation of net *primary productivity*).

Aquaculture

Aquaculture is a major agricultural industry in Texas. According to the Texas Aquaculture Association: "The aquaculture industry makes a total economic impact of over $US135 million to the state's economy, considering all the spin-offs" (Treece

2007:1). While this sector has the ability to contribute significantly to the energy budget in terms of HANPP the methods to calculate $NPP_{aquatic}$ as well as harvested $NPP_{aquatic}$ vary greatly from those for terrestrial NPP. Duarte and Cebrian (1996) discuss how the differences in biomass life cycles necessitates different methods to calculate aquatic NPP. Field et al. (1998) compare and contrast various methods to calculate both terrestrial and aquatic NPP in an attempt to estimate total global NPP. The fundamental differences in the lifecycles of terrestrial and aquatic biomass coupled with Field et al.'s methods would be impractical to implement spatially, as well as for harvested $NPP_{aquatic}$. HANPP from aquatic industries in Texas therefore deviates beyond the practical bounds of this study. Further research, investigating the extent of aquaculture in HANPP, would prove a useful contribution to the sustainability debate.

Land-Cover Change

Assessments of HANPP using methods similar to those employed here could also explicitly account for land-cover change from urban and infrastructure expansion if a long time series were being analyzed. This research normalized the six years of available data into a single dataset. Taking the data as a time series could have possibly provided some insights on changing patterns or offered some explanatory power for variations in model variables (Prince et al. 2001). A time series though must account for other variables not readily captured in the databases this study draws from. There are a number of external factors influencing NPP that can potentially bias harvested NPP. Prince et al. (2001:1203) identify climate and crop management practices as two highly influential inputs that must be recognized and accounted for in a time series. Though climate can be modeled, management practices can be extremely complicated and hard to model for the breadth of agricultural activities in this study.

Fossil Fuel

The methods presented here, as well as the majority of other HANPP research (Field 2001; Haberl 1997; Krausmann 2001; Rojstaczer, Sterling, and Moore 2001; Vitousek et al. 1986; Wright 1990), do not model NPP from fossil fuel. In modern society the overwhelming majority of NPP consumed by humans is in the form of fossil fuel (Dukes 2003). Dukes attempted to explicitly model HANPP from fossil fuel but due to the environmental conditions required to convert biomass to coal, oil, or natural gas he was unable to conclusively model the amount of modern biomass required to sustain consumption. Given the complexity of including fossil fuel in this study, it was not included. The methods required to model HANPP from fossil fuel consumption are relatively unexplored. Secondly, the geographical variation between where sequestered carbon which will become fossil fuel is located and where society is appropriating it could severely bias the results (the majority of fossil fuels coming from out-of-state). Because of the uncertainties outlined in Dukes' study, as well as his uncertainties, it was not replicated in this research.

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APPENDIX A

MODEL PARAMETERS

Data Source	**Timber**	**Reported Unit**	***MRY****	***MC***	***HI***	***fAG***	***C***	**References**
TFS	**Hardwood**	Cubic Feet	19958.064	0.523	0.963	0.869	0.497	(Birdsey 1992 [MC, HI, fAG, C])
	Pine	Cubic Feet	14968.548	0.510	0.930	0.786	0.531	(Birdsey 1992 [MC, HI, fAG, C])
2002	**Christmas****	Number	n/a	n/a	n/a	0.786	0.531	(Birdsey 1992 [MC, HI, fAG, C])
	Woody Crop***	Acres	907.185	n/a	0.600	0.800	0.450	(Birdsey 1992 [MC, fAG, C]; Scarascia-Mugnozza et al. 1997 [HI])

*MRY assumes lb/ft3 as 33.0 for Pine and 44.0 for Hardwood (Birdsey 1992)
**30kg dry weight 3-4in dbh (Jenkins et al. 2003)
***4-7 dry tons/acre (Alig et al. 2000)

Data Source	**Crop**	**Reported Unit**	***MRY* (to g)**	***MC* (%)**	***HI***	***fAG***	***C****	**References**
Annual	**Corn Grain**	Bushel	25401	11	0.45	0.85	0.45	(Lobell et al. 2002 [MRY, MC, HI, fAG])
	Oat	Bushel	14515	11	0.40	0.71	0.45	(Lobell et al. 2002 [MRY, MC, HI, fAG])
	Rice	Hundredweight	45359	9	0.40	0.80	0.45	(Lobell et al. 2002 [MRY, MC, HI, fAG])
	Sorghum	Bushel	25401	10	0.40	0.80	0.45	(Lobell et al. 2002 [MRY, MC, HI, fAG])
	Wheat	Bushel	27216	11	0.40	0.83	0.45	(Lobell et al. 2002 [MRY, MC, HI, fAG])
2002	**Proso Millet**	Bushel	23859	9	0.45	0.75	0.45	(USDA 2006 [MC]; Andales, Ahuja, and Peterson 2003 [HI, fAG])
	Rye	Bushel	25401	11	0.35	0.76	0.45	(USDA 2006 [MC]; Bradford, Lauenroth, and Burke 2005 [HI, fAG])

* constant from: (Lobell et al. 2002)

Data Source	**Crop**	**Reported Unit**	***MRY* (to g)**	***MC* (%)**	***HI***	***fAG***	***C****	**Refrences**
Annual	**Cotton**	Bale	217700	8	0.40	0.80	0.45	(Lobell et al. 2002 [MRY, MC, HI, fAG])
	Peanut	Pound	453	9	0.40	0.80	0.45	(Lobell et al. 2002 [MRY, MC, HI, fAG])
	Soybean	Bushel	27216	10	0.40	0.87	0.45	(Lobell et al. 2002 [MRY, MC, HI, fAG])
	Sugarcane	Ton	907185	85	0.93	0.92	0.45	(Lobell et al. 2002 [MC, HI]; Martin, Leonard, and Stamp 1976 [fAG])
	Sunflower	Pound	453	10	0.35	0.94	0.45	(Lobell et al. 2002 [MRY, MC, HI, fAG])
2002	**Beans**	Hundredweight	45359	79	0.50	0.50	0.45	(USDA 2006 [MC]; Stockle and Nelson 1996 [HI]; Bradford, Lauenroth, and Burke 2005 [fAG])
	CowPea	Bushel	27216	77	0.50	0.50	0.45	(USDA 2006 [MC]; Stockle and Nelson 1996 [HI]; Bradford, Lauenroth, and Burke 2005 [fAG])
	Guar	Pounds	453	14	0.4	0.8	0.45	(Department of Horticulture and Landscape Architecture 1999 [MC], Lobell et al. 2002 [HI, fAG])
	Pea	Hundredweight	45359	79	0.50	0.50	0.45	(USDA 2006 [MC]; Stockle and Nelson 1996 [HI]; Bradford, Lauenroth, and Burke 2005 [fAG])
	Potato	Hundredweight	45359	75	0.55	0.90	0.45	(USDA 2006 [MC]; Bradford, Lauenroth, and Burke 2005 [HI, fAG])
	Sweet Potato	Hundredweight	45359	77	0.55	0.90	0.45	(USDA 2006 [MC]; Bradford, Lauenroth, and Burke 2005 [HI, fAG])

* constant from: (Lobell et al. 2002)

Data Source	Crop	Reported Unit	*MRY* (to g)	*MC* (%)	*HI*	*fAG*	*C**	Refrences
Annual	**Corn Silage**	Tons	907185	65	1.0	0.85	0.45	(Lobell et al. 2002 [MRY, MC, HI, fAG])
2002	**Bahia Grass Seed**	Pounds	453	13	0.4	0.8	0.45	(Elias, Garay, and Chastain 2002 [MC]; Lobell et al. 2002 [HI, fAG])
	Hay, All	Dry Tons	907185	15	1.0	0.53	0.45	(Lobell et al. 2002 [MRY, MC, HI, fAG])
	Haylage, All	Green Tons	907185	65	1.0	0.8	0.45	(Ball et al. 2001 [MC]; Lobell et al. 2002 [HI]; Hicke et al. 2002 [fAG])
	Other Seed	Pounds	453	13	0.4	0.8	0.45	(Elias, Garay, and Chastain 2002 [MC]; Lobell et al. 2002 [HI, fAG])
	Rye Grass Seed	Pounds	453	35	0.4	0.8	0.45	(Ag-Infor Centre 2002 [MC]; Lobell et al. 2002 [HI, fAG])
	Sorghum Silage	Tons	907185	65	1.0	0.8	0.45	(Ball et al. 2001 [MC]; Lobell et al. 2002 [HI]; Hicke et al. 2002 [fAG])

* constant from: (Lobell et al. 2002)

Data Source	Crop	Reported Unit	Yield	*MRY* (to g)	*MC* (%)	*HI*	*fAG*	*C**	References
2002	**Cabbage**	Hundredweight	373	45359	92	1	0.8	0.45	(USDA 2007a [Yield]; 2006 [MC]; Lobell et al. 2002 [fAG])
	Cantaloupe	Pounds	40.0	453	90	0.40	0.71	0.45	(Klostermann 2003 [Yield]; USDA 2006 [MC]; Valantin et al. 1999 [HI]; Vavrina 1998 [fAG])
	Carrot	Hundredweight	16.46	45359	88	n/a	0.3	0.45	(USDA 2007d [Yield]; 2006 [MC]; Antonious and Kasperbauer 2002 [fAG])
	Chilipepper	Hundredweight	50	45359	88	0.5	0.8	0.45	(USDA 2007c [Yield]; 2006 [MC]; Lobell et al. 2002 [fAG])
	Cucumber	Tons	5.98	907185	95	0.6	0.9	0.45	(Rhodes 2006 [Yield]; USDA 2006 [MC]; Marcelis 1992 [HI]; Kharkina, Ottosen, and Rosenqvist 1999 [fAG])
	Onion	Hundredweight	316	45359	89	n/a	0.8	0.45	(USDA 2007b [Yield]; 2006 [MC]; Brewster 1982 [fAG])
	Pumpkin	Pounds	20000	453	92	0.97	0.7	0.45	(Dainello 2003 [Yield]; USDA 2006 [MC]; Edelson, Duthie, and Roberts 2003 [HI];

									Vavrina 1998 [fAG])
	Snap Beans	Bushel	275	13608	90	0.5	0.5	0.45	(Department of Horticulture and Landscape Architecture 1999 [Yield]; USDA 2006 [MC]; Bradford, Lauenroth, and Burke 2005 [HI, fAG])
	Spinach	Hundredweight	126	45359	91	1	0.8	0.45	(Rhodes 2006 [Yield]; USDA 2006 [MC]; Lobell et al. 2002 [fAG])
	Sweet Corn	Hundredweight	319.5	45359	76	0.45	0.85	0.45	(USDA 2007e [Yield]; 2006 [MC]; Hay 1995 [HI, fAG])
	Tomato	Hundredweight	160	45359	95	0.62	0.8	0.45	(USDA 2007f [Yield]; 2006 [MC]; Scholberg et al. 2000 [HI]; Lobell et al. 2002 [fAG])
	Watermelon	Hundredweight	160.0	45359	91	0.97	0.74	0.45	(USDA 2007g [Yield]; 2006 [MC]; Edelson, Duthie, and Roberts 2003 [HI]; Vavrina 1998 [fAG])

* constant from: (Lobell et al. 2002)

Data Source	**Crop**	**Reported Unit**	**Yield**	***MRY* (to g)**	***MC* (%)**	***HI***	***fAG****	***C*****	**References**
2002	**Citrus**	Tons	12.1	907185	82	0.03	n/a	0.45	(USDA 2004b [Yield]; 2006 [MC]; Clark et al. 2001 [HI])
	Grape	Tons	2.4	907185	81	0.03	n/a	0.45	(NASS 2006 [Yield]; USDA 2006 [MC]; Clark et al. 2001 [HI])
	Peaches	Pounds	4600.0	453	89	0.03	n/a	0.45	(Smith and Anciso 2005 [Yield]; USDA 2006 [MC]; Clark et al. 2001 [HI])
	Pecan	Pounds	1000.0	453	4	0.03	n/a	0.45	(Aldred et al. 1997 [Yield]; USDA 2006 [MC]; Clark et al. 2001 [HI])

* roots not harvested
** constant from: (Lobell et al. 2002)

APPENDIX B

TABLE OF RESULTS

- Carbon/ P (Production) in tons
- NPP in grams per square meter

Totals

County	Area (km^2)	Carbon Available	Carbon Harvested	Carbon Remaining	HANPP (%)
Anderson	2,797	1,457,510	157,627	1,299,883	10.81
Andrews	3,896	733,288	29,555	703,733	4.03
Angelina	2,247	1,201,229	168,829	1,032,400	14.05
Aransas	741	358,830	45,875	312,955	12.78
Archer	2,396	796,546	66,520	730,026	8.35
Armstrong	2,368	572,760	80,217	492,542	14.01
Atascosa	3,198	1,916,649	65,119	1,851,530	3.40
Austin	1,701	1,047,026	100,225	946,801	9.57
Bailey	2,148	421,107	123,438	297,669	29.31
Bandera	2,064	1,340,550	11,313	1,329,237	0.84
Bastrop	2,320	1,435,153	75,860	1,359,294	5.29
Baylor	2,332	587,850	56,821	531,029	9.67
Bee	2,279	1,391,393	89,145	1,302,248	6.41
Bell	2,817	1,321,172	271,774	1,049,398	20.57
Bexar	3,253	1,965,600	97,459	1,868,141	4.96
Blanco	1,847	1,068,559	10,488	1,058,071	0.98
Borden	2,348	517,424	10,970	506,454	2.12
Bosque	2,596	1,179,655	82,979	1,096,676	7.03
Bowie	2,404	979,308	202,076	777,233	20.63
Brazoria	3,856	3,423,707	153,655	3,270,052	4.49
Brazos	1,529	885,656	29,528	856,128	3.33
Brewster	16,094	3,728,184	2,997	3,725,187	0.08
Briscoe	2,335	604,251	70,885	533,366	11.73
Brooks	2,442	1,332,865	10,987	1,321,878	0.82
Brown	2,476	959,462	63,186	896,275	6.59
Burleson	1,756	1,017,211	47,795	969,416	4.70
Burnet	2,643	1,424,978	19,121	1,405,857	1.34
Caldwell	1,417	846,274	67,996	778,278	8.03
Calhoun	1,065	675,080	69,714	605,366	10.33
Callahan	2,332	773,458	36,616	736,842	4.73
Cameron	2,481	987,740	373,920	613,819	37.86
Camp	528	243,347	18,791	224,556	7.72
Carson	2,394	543,631	213,280	330,352	39.23
Cass	2,498	882,226	242,181	640,045	27.45
Castro	2,333	646,069	594,550	51,519	92.03
Chambers	1,649	1,194,214	95,103	1,099,111	7.96
Cherokee	2,758	1,363,386	202,057	1,161,329	14.82
Childress	1,848	428,864	30,731	398,133	7.17
Clay	2,886	1,058,957	64,514	994,443	6.09
Cochran	2,013	362,867	105,087	257,780	28.96
Coke	2,403	644,900	4,705	640,196	0.73
Coleman	3,317	1,067,745	59,986	1,007,759	5.62
Collin	2,295	859,125	216,928	642,197	25.25
Collingsworth	2,380	558,017	56,646	501,371	10.15
Colorado	2,524	1,586,434	228,138	1,358,296	14.38
Comal	1,487	1,000,082	17,507	982,575	1.75
Comanche	2,453	897,887	229,866	668,021	25.60
Concho	2,572	796,156	36,554	759,603	4.59
Cooke	2,323	1,154,921	166,676	988,244	14.43
Coryell	2,736	1,230,463	97,151	1,133,311	7.90
Cottle	2,334	577,314	11,667	565,647	2.02
Crane	2,039	302,593	1,204	301,388	0.40
Crockett	7,277	2,239,375	1,709	2,237,666	0.08
Crosby	2,336	498,159	93,184	404,976	18.71
Culberson	9,936	1,442,056	9,233	1,432,823	0.64
Dallam	3,906	911,468	847,360	64,107	92.97
Dallas	2,354	873,439	43,056	830,383	4.93
Dawson	2,339	421,672	114,517	307,155	27.16
Deaf Smith	3,887	825,334	337,361	487,973	40.88
Delta	721	312,925	61,467	251,458	19.64
Denton	2,481	1,089,559	138,614	950,945	12.72
DeWitt	2,358	1,507,074	73,003	1,434,071	4.84
Dickens	2,344	596,402	26,120	570,283	4.38
Dimmit	3,454	1,413,286	7,624	1,405,662	0.54

Donley	2,416	579,177	43,581	535,596	7.52
Duval	4,648	2,332,186	34,739	2,297,446	1.49
Eastland	2,412	979,223	87,991	891,232	8.99
Ector	2,340	386,433	2,498	383,935	0.65
Edwards	5,489	2,631,666	1,651	2,630,015	0.06
El Paso	2,656	326,799	94,399	232,399	28.89
Ellis	2,465	1,020,781	234,620	786,161	22.98
Erath	2,820	1,164,926	167,500	997,426	14.38
Falls	2,005	1,003,598	252,313	751,285	25.14
Fannin	2,332	1,095,754	206,898	888,856	18.88
Fayette	2,486	1,525,064	133,516	1,391,548	8.75
Fisher	2,335	577,186	37,270	539,916	6.46
Floyd	2,572	572,140	211,603	360,537	36.98
Foard	1,832	469,294	61,169	408,125	13.03
Fort Bend	2,299	1,538,795	185,778	1,353,017	12.07
Franklin	765	353,036	42,894	310,142	12.15
Freestone	2,313	1,203,359	2,432	1,200,927	0.20
Frio	2,935	1,649,029	70,897	1,578,132	4.30
Gaines	3,900	726,022	321,586	404,435	44.29
Galveston	1,065	714,832	14,901	699,931	2.08
Garza	2,322	534,512	19,062	515,450	3.57
Gillespie	2,747	1,535,426	45,694	1,489,732	2.98
Glasscock	2,335	519,349	41,074	478,275	7.91
Goliad	2,225	1,391,944	35,900	1,356,044	2.58
Gonzales	2,770	1,740,101	103,987	1,636,114	5.98
Gray	2,406	579,646	91,086	488,560	15.71
Grayson	2,536	1,180,850	201,085	979,765	17.03
Gregg	718	342,334	31,788	310,546	9.29
Grimes	2,078	1,257,398	77,867	1,179,531	6.19
Guadalupe	1,849	1,089,831	164,565	925,266	15.10
Hale	2,605	610,165	359,134	251,030	58.86
Hall	2,341	545,735	29,723	516,012	5.45
Hamilton	2,165	874,892	77,252	797,640	8.83
Hansford	2,384	600,454	373,870	226,584	62.26
Hardeman	1,803	472,858	54,583	418,275	11.54
Hardin	2,334	1,816,237	165,028	1,651,208	9.09
Harris	4,607	2,804,961	98,568	2,706,393	3.51
Harrison	2,379	1,002,797	169,896	832,901	16.94
Hartley	3,796	847,840	703,624	144,216	82.99
Haskell	2,356	552,495	131,552	420,942	23.81
Hays	1,759	1,076,958	25,520	1,051,438	2.37
Hemphill	2,361	597,766	36,301	561,464	6.07
Henderson	2,461	1,093,868	122,241	971,627	11.18
Hidalgo	4,099	1,941,316	913,598	1,027,718	47.06
Hill	2,553	1,026,886	337,392	689,495	32.86
Hockley	2,357	445,866	143,532	302,335	32.19
Hood	1,131	438,088	57,962	380,126	13.23
Hopkins	2,056	970,258	195,375	774,884	20.14
Houston	3,209	1,834,045	182,844	1,651,200	9.97
Howard	2,343	551,698	36,420	515,278	6.60
Hudspeth	11,938	1,724,822	12,047	1,712,775	0.70
Hunt	2,287	1,001,569	152,952	848,616	15.27
Hutchinson	2,319	529,081	129,598	399,483	24.49
Irion	2,724	764,670	2,556	762,114	0.33
Jack	2,382	1,158,217	4,737	1,153,480	0.41
Jackson	2,221	1,360,545	271,076	1,089,469	19.92
Jasper	2,524	1,862,720	266,375	1,596,345	14.30
Jeff Davis	5,894	1,355,375	3,016	1,352,359	0.22
Jefferson	2,576	1,771,993	102,048	1,669,945	5.76
Jim Hogg	2,941	1,359,630	2,322	1,357,308	0.17
Jim Wells	2,248	1,203,577	121,251	1,082,326	10.07
Johnson	1,902	827,225	128,066	699,159	15.48
Jones	2,426	545,201	97,032	448,169	17.80
Karnes	1,951	1,145,161	67,215	1,077,945	5.87
Kaufman	2,091	960,375	117,930	842,446	12.28
Kendall	1,716	980,754	1,594	979,160	0.16
Kenedy	3,568	1,979,544	6,740	1,972,804	0.34
Kent	2,338	614,365	9,119	605,247	1.48
Kerr	2,867	1,711,016	12,413	1,698,603	0.73
Kimble	3,238	1,563,981	6,658	1,557,322	0.43
King	2,364	613,911	7,475	606,435	1.22
Kinney	3,535	1,620,043	1,560	1,618,483	0.10
Kleberg	2,277	1,168,275	93,861	1,074,414	8.03
Knox	2,214	556,842	105,631	451,211	18.97
La Salle	3,867	1,880,090	9,945	1,870,145	0.53
Lamar	2,417	1,116,420	197,704	918,717	17.71
Lamb	2,640	606,333	344,887	261,446	56.88
Lampasas	1,848	861,814	29,805	832,009	3.46
Lavaca	2,513	1,618,027	119,680	1,498,347	7.40
Lee	1,643	980,930	60,794	920,136	6.20
Leon	2,802	1,575,248	102,160	1,473,088	6.49
Liberty	3,056	2,178,387	236,449	1,941,938	10.85
Limestone	2,418	1,196,703	100,509	1,096,194	8.40

Lipscomb	2,413	591,941	59,991	531,951	10.13
Live Oak	2,792	1,556,873	53,596	1,503,276	3.44
Llano	2,501	1,343,042	10,121	1,332,921	0.75
Loving	1,760	244,058	873	243,185	0.36
Lubbock	2,335	476,915	157,167	319,748	32.95
Lynn	2,316	450,260	95,638	354,623	21.24
Madison	1,225	727,928	39,138	688,789	5.38
Marion	1,093	355,052	87,910	267,141	24.76
Martin	2,374	456,879	46,171	410,708	10.11
Mason	2,412	1,231,294	22,001	1,209,293	1.79
Matagorda	3,144	2,014,091	212,221	1,801,870	10.54
Maverick	3,346	1,378,479	15,440	1,363,039	1.12
McCulloch	2,778	1,198,916	36,593	1,162,323	3.05
McLennan	2,746	1,260,446	296,853	963,593	23.55
McMullen	2,958	1,635,751	6,096	1,629,655	0.37
Medina	3,453	2,125,192	181,057	1,944,135	8.52
Menard	2,336	1,080,793	11,029	1,069,764	1.02
Midland	2,339	427,411	19,564	407,846	4.58
Milam	2,647	1,470,897	224,621	1,246,276	15.27
Mills	1,941	826,727	48,507	778,219	5.87
Mitchell	2,372	590,386	28,214	562,172	4.78
Montague	2,426	1,113,758	81,055	1,032,702	7.28
Montgomery	2,795	1,831,681	115,102	1,716,579	6.28
Moore	2,358	543,861	507,685	36,176	93.35
Morris	672	291,962	18,651	273,311	6.39
Motley	2,563	641,339	9,724	631,615	1.52
Nacogdoches	2,550	1,275,982	207,843	1,068,138	16.29
Navarro	2,815	1,256,313	141,267	1,115,046	11.24
Newton	2,452	1,778,683	196,824	1,581,858	11.07
Nolan	2,366	671,296	19,529	651,767	2.91
Nueces	2,175	890,559	384,598	505,961	43.19
Ochiltree	2,377	549,246	310,742	238,503	56.58
Oldham	3,896	760,544	50,214	710,330	6.60
Orange	988	766,251	34,973	731,278	4.56
Palo Pinto	2,551	1,394,421	56,205	1,338,216	4.03
Panola	2,137	968,334	177,353	790,981	18.32
Parker	2,356	1,066,454	95,663	970,791	8.97
Parmer	2,298	574,236	441,965	132,271	76.97
Pecos	12,370	2,385,946	29,338	2,356,608	1.23
Polk	2,883	1,792,528	250,206	1,542,322	13.96
Potter	2,390	511,372	31,196	480,176	6.10
Presidio	10,045	2,119,678	4,763	2,114,915	0.22
Rains	672	283,710	632	283,078	0.22
Randall	2,391	546,118	107,538	438,580	19.69
Reagan	3,047	620,435	15,295	605,140	2.47
Real	1,812	1,295,671	3,696	1,291,975	0.29
Red River	2,752	1,224,655	159,167	1,065,488	13.00
Reeves	6,870	898,808	22,365	876,442	2.49
Refugio	2,119	1,324,104	93,784	1,230,319	7.08
Roberts	2,394	580,510	35,955	544,555	6.19
Robertson	2,244	1,254,722	127,900	1,126,822	10.19
Rockwall	385	136,849	36,789	100,060	26.88
Runnels	2,736	698,807	110,010	588,797	15.74
Rusk	2,438	1,163,496	156,344	1,007,151	13.44
Sabine	1,490	713,681	87,075	626,606	12.20
San Augustine	1,541	832,427	120,835	711,591	14.52
San Jacinto	1,630	933,861	84,533	849,328	9.05
San Patricio	1,830	885,755	282,147	603,608	31.85
San Saba	2,946	1,535,567	86,087	1,449,480	5.61
Schleicher	3,393	1,184,536	10,396	1,174,139	0.88
Scurry	2,351	559,998	37,532	522,465	6.70
Shackelford	2,370	654,357	21,260	633,097	3.25
Shelby	2,166	1,046,991	155,985	891,006	14.90
Sherman	2,393	584,694	592,137	-7,444	101.27
Smith	2,464	1,172,157	149,836	1,022,321	12.78
Somervell	497	225,471	14,386	211,084	6.38
Starr	3,181	1,429,053	75,174	1,353,879	5.26
Stephens	2,384	915,157	4,586	910,571	0.50
Sterling	2,392	614,395	3,756	610,639	0.61
Stonewall	2,383	621,454	16,685	604,769	2.68
Sutton	3,766	1,448,148	2,544	1,445,604	0.18
Swisher	2,335	564,955	201,018	363,937	35.58
Tarrant	2,324	932,592	44,593	887,999	4.78
Taylor	2,379	685,402	73,173	612,228	10.68
Terrell	6,117	1,637,024	1,594	1,635,430	0.10
Terry	2,311	425,033	157,987	267,046	37.17
Throckmorton	2,369	662,878	32,554	630,324	4.91
Titus	1,105	513,957	49,076	464,881	9.55
Tom Green	3,989	1,096,678	104,682	991,996	9.55
Travis	2,646	1,461,126	85,476	1,375,650	5.85
Trinity	1,854	1,057,701	117,526	940,174	11.11
Tyler	2,432	1,670,332	236,121	1,434,211	14.14
Upshur	1,540	689,350	110,109	579,241	15.97

Upton	3,221	513,187	8,551	504,636	1.67
Uvalde	4,035	2,339,036	112,612	2,226,424	4.81
Val Verde	8,390	3,030,348	6,944	3,023,404	0.23
Van Zandt	2,228	1,061,696	133,218	928,478	12.55
Victoria	2,301	1,477,300	156,035	1,321,265	10.56
Walker	2,080	1,257,166	101,652	1,155,514	8.09
Waller	1,345	818,441	119,939	698,502	14.65
Ward	2,173	312,722	1,262	311,461	0.40
Washington	1,611	952,166	82,978	869,188	8.71
Webb	8,740	3,904,571	10,870	3,893,701	0.28
Wharton	2,837	1,759,923	587,519	1,172,405	33.38
Wheeler	2,370	579,809	43,985	535,824	7.59
Wichita	1,638	483,069	100,442	382,627	20.79
Wilbarger	2,532	664,377	166,415	497,962	25.05
Willacy	1,548	697,435	215,483	481,953	30.90
Williamson	2,937	1,489,020	318,926	1,170,094	21.42
Wilson	2,093	1,259,817	119,181	1,140,636	9.46
Winkler	2,185	346,703	1,451	345,252	0.42
Wise	2,389	1,045,541	142,520	903,021	13.63
Wood	1,806	767,948	113,653	654,296	14.80
Yoakum	2,077	378,850	122,435	256,415	32.32
Young	2,409	949,239	48,888	900,351	5.15
Zapata	2,738	1,288,091	1,152	1,286,940	0.09
Zavala	3,369	1,573,105	42,604	1,530,501	2.71

Timber Industry

County	Area (Km^2)	Christmas Trees		Short-Rotation Woody Crops		Timber	
		P	NPP	P	NPP	P	NPP
Anderson	2,797	26	25	2	1	62,441	150,964
Angelina	2,247			0	1	167,917	480,363
Bastrop	2,320			0	1		
Bowie	2,404					83,638	262,333
Brazoria	3,856			0	1		
Camp	528					13,543	430,088
Cass	2,498	30	39	1	1	201,510	451,101
Chambers	1,649					14,853	513,579
Cherokee	2,758	0	2	2	1	127,213	317,586
Denton	2,481	12	303				
Franklin	765					4,076	41,038
Galveston	1,065			0	1		
Gregg	718					23,616	275,607
Grimes	2,078					11,660	92,053
Guadalupe	1,849	111	451				
Hardin	2,334	41	157			158,502	376,464
Harris	4,607	105	91	0	1	29,861	127,602
Harrison	2,379			0	1	129,997	350,856
Henderson	2,461					14,559	90,655
Houston	3,209	26	140	0	1	88,120	236,183
Hunt	2,287			1	1		
Jasper	2,524					243,987	508,728
Jefferson	2,576					11,153	139,313
Leon	2,802					8,738	26,088
Liberty	3,056	69	180			118,578	301,750
Madison	1,225					555	6,766
Marion	1,093					77,152	345,193
Montague	2,426	8	56				
Montgomery	2,795					91,044	214,832
Morris	672					18,366	223,606
Nacogdoches	2,550					155,310	343,978
Navarro	2,815	103	345	0	1		
Newton	2,452	81	1,178			187,058	349,264
Orange	988	55	180			19,746	167,703
Panola	2,137					133,847	373,586
Polk	2,883			0	1	228,615	435,198
Red River	2,752					54,002	161,823
Rusk	2,438	15	77	1	1	98,593	327,170
Sabine	1,490					86,476	322,072
San Augustine	1,541					120,154	456,731
San Jacinto	1,630					70,650	246,689
Shelby	2,166					118,252	357,931
Smith	2,464	154	65	0	1	55,441	225,559
Titus	1,105					14,987	143,928
Travis	2,646	18	501				
Trinity	1,854					92,672	278,794
Tyler	2,432					219,145	449,324
Upshur	1,540	12	149			57,359	275,993
Van Zandt	2,228			0	1	4,480	33,023
Walker	2,080			0	1	67,220	204,523
Waller	1,345					746	12,164
Wise	2,389	83	267				
Wood	1,806					19,689	87,897

Grain

County	Area (Km²)	Corn for grain		Oat		Proso Millet		Rice	
		P	NPP	P	NPP	P	NPP	P	NPP
Anderson	2,797	147	491	32	261			268	838
Andrews	3,896	801	908	50	143				
Angelina	2,247	58	488	14	164			152	886
Aransas	741	559	345	27	202				
Archer	2,396	105	564	448	201				
Armstrong	2,368	4,118	1,053	308	201				
Atascosa	3,198	6,427	588	157	155				
Austin	1,701	7,544	499	146	197			9,587	1,069
Bailey	2,148	19,867	1,151	129	144				
Bandera	2,064	77	651	93	183				
Bastrop	2,320	2,912	480	112	185				
Baylor	2,332	96	756	2,283	232				
Bee	2,279	28,977	355	253	198				
Bell	2,817	134,134	503	2,206	226				
Bexar	3,253	21,352	470	828	151				
Blanco	1,847	69	651						
Borden	2,348	236	715	465	164				
Bosque	2,596	3,777	683	1,980	222				
Bowie	2,404	23,706	684	27	261			4,895	806
Brazoria	3,856	5,820	575	17	139			61,799	1,048
Brazos	1,529	12,811	676	10	164			103	886
Brewster	16,094	168	891	263	220				
Briscoe	2,335	12,101	867	113	185				
Brooks	2,442	4,255	501	21	145				
Brown	2,476	109	564	2,218	191				
Burleson	1,756	27,620	663	249	194				
Burnet	2,643	98	651	199	155				
Caldwell	1,417	9,703	411	298	192				
Calhoun	1,065	30,945	604	5	139			6,182	764
Callahan	2,332	103	564	452	209				
Cameron	2,481	42,740	639	4	202				
Camp	528	4,539	765	6	261			51	838
Carson	2,394	50,134	1,161	791	255				
Cass	2,498	131	491	28	261			239	838
Castro	2,333	341,834	1,288	274	141				
Chambers	1,649	2,846	391	29	71			40,970	776
Cherokee	2,758	145	491	31	261			264	838
Childress	1,848	186	715	164	135				
Clay	2,886	127	564	247	122				
Cochran	2,013	6,862	1,304	110	90				
Coke	2,403	89	651	332	170				
Coleman	3,317	137	756	3,412	150				
Collin	2,295	76,695	590	965	304				
Collingsworth	2,380	240	715	227	164				
Colorado	2,524	27,518	593	254	105			134,162	1,052
Comal	1,487	1,995	419	69	170				
Comanche	2,453	2,330	626	1,086	230				
Concho	2,572	1,516	624	716	163				
Cooke	2,323	4,614	552	6,326	359				
Coryell	2,736	12,465	429	7,407	252				
Cottle	2,334	235	715	246	202				
Crane	2,039	21	891	121	220				
Crockett	7,277	271	651	115	183				
Crosby	2,336	851	701	75	153				
Culberson	9,936	104	891	92	228				
Dallam	3,906	662,923	1,249	379	234				
Dallas	2,354	7,974	485	802	220				
Dawson	2,339	481	908	133	164				
Deaf Smith	3,887	77,715	1,066	840	196				
Delta	721	12,944	589	802	220				
Denton	2,481	9,277	460	1,515	264				
DeWitt	2,358	2,168	369	146	197				
Dickens	2,344	236	715	92	228				
Dimmit	3,454	2,793	575	44	164				
Donley	2,416	4,222	948	231	164				
Duval	4,648	1,809	271	133	141				
Eastland	2,412	106	564	541	191				
Ector	2,340	24	891	139	220				
Edwards	5,489	204	651	87	183				
El Paso	2,656	5,816	1,268	624	220				
Ellis	2,465	68,299	555	1,491	307				
Erath	2,820	1,090	449	474	195				
Falls	2,005	161,311	575	4,890	214				
Fannin	2,332	33,715	564	935	217				
Fayette	2,486	18,985	480	27	202				
Fisher	2,335	97	756	123	202				
Floyd	2,572	24,048	1,055	643	199				
Foard	1,832	184	715	417	196				
Fort Bend	2,299	30,018	556					32,912	1,006
Franklin	765	40	491	9	261			73	838
Freestone	2,313	228	488					156	886
Frio	2,935	10,936	734	1,605	187				
Gaines	3,900	7,899	1,148	50	143				
Galveston	1,065	390	482	5	139			4,644	1,147

Garza	2,322	234	715	460	164				
Gillespie	2,747	3,302	466	3,524	220				
Glasscock	2,335	480	908	30	143				
Goliad	2,225	9,637	441	46	162				
Gonzales	2,770	8,515	487	60	148				
Gray	2,406	20,989	1,161						
Grayson	2,536	39,367	557	959	219				
Gregg	718	38	491	8	261			69	838
Grimes	2,078	3,524	502	13	164			140	886
Guadalupe	1,849	31,277	390	220	218				
Hale	2,605	94,484	1,111	372	170	1,125	297		
Hall	2,341	236	715	223	164				
Hamilton	2,165	3,364	723	10,587	263				
Hansford	2,384	159,410	1,281	604	187				
Hardeman	1,803	181	715	926	164				
Hardin	2,334	60	488	15	164			2,844	639
Harris	4,607	11,583	549	20	139			7,401	938
Harrison	2,379	125	491	27	261			228	838
Hartley	3,796	554,902	1,280	122	201				
Haskell	2,356	97	756	784	237				
Hays	1,759	5,918	402	163	183				
Hemphill	2,361	4,118	1,053	479	201				
Henderson	2,461	129	491	28	261			235	838
Hidalgo	4,099	39,726	465	6	202				
Hill	2,553	93,929	585	1,183	258				
Hockley	2,357	485	908	90	148				
Hood	1,131	50	564	95	195				
Hopkins	2,056	4,521	399	82	202			4,789	910
Houston	3,209	4,823	550	164	202			307	838
Howard	2,343	482	908	30	143				
Hudspeth	11,938	1,596	986	379	281				
Hunt	2,287	12,617	532	454	259				
Hutchinson	2,319	56,974	1,292	471	201				
Irion	2,724	101	651	43	183				
Jack	2,382	105	564	208	215				
Jackson	2,221	106,642	525	10	139			57,049	957
Jasper	2,524	65	488	16	164			170	886
Jeff Davis	5,894	61	891	96	220				
Jefferson	2,576	1,667	334	11	139			57,446	773
Jim Hogg	2,941	277	554	25	145				
Jim Wells	2,248	17,780	259	154	190				
Johnson	1,902	7,762	528	798	275				
Jones	2,426	100	756	530	164				
Karnes	1,951	13,369	285	206	179				
Kaufman	2,091	8,830	530	746	257				
Kendall	1,716	64	651	380	194				
Kenedy	3,568	2,318	554	31	145				
Kent	2,338	235	715	194	160				
Kerr	2,867	107	651	95	141				
Kimble	3,238	120	651	92	228				
King	2,364	238	715	926	164				
Kinney	3,535	131	651	144	198				
Kleberg	2,277	1,835	219						
Knox	2,214	92	756	1,351	238				
La Salle	3,867	365	554	212	165				
Lamar	2,417	45,657	597	92	228				
Lamb	2,640	113,327	1,112	344	212				
Lampasas	1,848	851	526	1,062	190				
Lavaca	2,513	8,613	412					6,578	895
Lee	1,643	2,425	467	306	239				
Leon	2,802	276	488	100	248			189	886
Liberty	3,056	11,033	350	13	139			32,892	825
Limestone	2,418	23,219	518	1,331	270				
Lipscomb	2,413	17,997	1,230	72	177				
Live Oak	2,792	11,312	324	60	177				
Llano	2,501	93	651	506	183				
Loving	1,760	18	891	105	220				
Lubbock	2,335	480	908	231	143	210	227		
Lynn	2,316	476	908	184	91				
Madison	1,225	121	488	8	164			83	886
Marion	1,093	57	491	12	261			105	838
Martin	2,374	488	908	30	143				
Mason	2,412	90	651	231	180				
Matagorda	3,144	9,584	488	14	139			87,842	948
Maverick	3,346	316	554	169	119				
McCulloch	2,778	4,362	599	1,754	167				
McLennan	2,746	122,928	538	8,563	310				
McMullen	2,958	279	554						
Medina	3,453	60,617	619	7,105	226				
Menard	2,336	87	651	506	183				
Midland	2,339	481	908	30	143				
Milam	2,647	93,530	511	1,057	241				
Mills	1,941	85	564	2,871	211				
Mitchell	2,372	98	756	20	73				
Montague	2,426	107	564	211	215				
Montgomery	2,795	72	488	18	164			189	886
Moore	2,358	336,244	1,269	350	185				
Morris	672	35	491					64	838

Motley	2,563	258	715	245	164			
Nacogdoches	2,550	134	491	29	261		244	838
Navarro	2,815	22,775	583	717	266			
Newton	2,452	63	488	16	164		166	886
Nolan	2,366	98	756	406	262			
Nueces	2,175	24,034	360	27	202			
Ochiltree	2,377	69,071	1,285	117	216			
Oldham	3,896	2,552	1,053	506	201			
Orange	988	390	482	4	139		5,069	864
Palo Pinto	2,551	112	564	196	194			
Panola	2,137	112	491	24	261		204	838
Parker	2,356	104	564	205	215			
Parmer	2,298	169,361	1,284	217	206			
Pecos	12,370	129	891	123	76			
Polk	2,883	75	488	18	164		195	886
Potter	2,390	1,566	1,053	311	201			
Presidio	10,045	105	891	164	220			
Rains	672	35	491	8	261		64	838
Randall	2,391	5,080	941	311	201			
Reagan	3,047	113	651	48	183			
Real	1,812	67	651	29	183			
Red River	2,752	19,774	646				3,947	975
Reeves	6,870	72	891	235	291			
Refugio	2,119	20,967	486					
Roberts	2,394	10,949	1,278	486	201			
Robertson	2,244	17,908	697	442	234		151	886
Rockwall	385	6,587	509	921	253			
Runnels	2,736	113	756	1,074	138			
Rusk	2,438	128	491	28	261		233	838
Sabine	1,490	38	488	10	164		101	886
San Augustine	1,541	40	488	10	164		104	886
San Jacinto	1,630	42	488	10	164		110	886
San Patricio	1,830	21,844	410					
San Saba	2,946	110	651	1,380	161			
Schleicher	3,393	126	651	536	156			
Scurry	2,351	97	756	133	117			
Shackelford	2,370	104	564	461	195			
Shelby	2,166	114	491	24	261		207	838
Sherman	2,393	365,731	1,257	573	210			
Smith	2,464	130	491	28	261		236	838
Somervell	497	22	564	624	215			
Starr	3,181	2,943	287	5	202			
Stephens	2,384	105	564	347	151			
Sterling	2,392	89	651	757	187			
Stonewall	2,383	99	756	409	253			
Sutton	3,766	140	651	164	202			
Swisher	2,335	45,981	1,100	312	161			
Tarrant	2,324	3,005	437					
Taylor	2,379	98	756	677	147			
Terrell	6,117	64	891	100	220			
Terry	2,311	6,144	779	30	143			
Throckmorton	2,369	104	564	386	238			
Titus	1,105	58	491	12	261		106	838
Tom Green	3,989	9,251	902	730	235			
Travis	2,646	18,462	420	256	210			
Trinity	1,854	48	488	12	164		125	886
Tyler	2,432	63	488	16	164		164	886
Upshur	1,540	81	491	17	261		147	838
Upton	3,221	120	651	51	183			
Uvalde	4,035	57,918	781	4,350	201			
Val Verde	8,390	312	651	133	183			
Van Zandt	2,228	117	491	25	261		213	838
Victoria	2,301	65,888	558	10	139		7,627	1,071
Walker	2,080	2,692	554	13	164		140	886
Waller	1,345	19,393	560	72	177		35,785	1,225
Ward	2,173	23	891	129	220			
Washington	1,611	1,707	346	41	101			
Webb	8,740	824	554	75	145			
Wharton	2,837	107,112	658	12	139		218,986	1,066
Wheeler	2,370	2,713	1,341					
Wichita	1,638	2,367	487	330	225			
Wilbarger	2,532	3,546	641	1,217	152			
Willacy	1,548	3,648	492	2	202			
Williamson	2,937	167,433	499	2,375	220			
Wilson	2,093	14,233	419	218	135			
Winkler	2,185	23	891	130	220			
Wise	2,389	2,075	394	122	165			
Wood	1,806	95	491	20	261		173	838
Yoakum	2,077	4,654	908	72	177			
Young	2,409	106	564	446	197			
Zapata	2,738	258	554	24	145			
Zavala	3,369	8,848	604	1,251	180			

Grain (continued)

County	Area (Km^2)	Rye		Sorghum		Wheat	
		P	NPP	P	NPP	P	NPP
Anderson	2,797			4,876	476	1,488	272
Andrews	3,896			3,041	241	1,368	220
Angelina	2,247			372	596	63	227
Aransas	741			44,121	501	55	210
Archer	2,396			486	364	18,320	192
Armstrong	2,368			29,051	340	26,708	198
Atascosa	3,198			4,206	348	1,997	183
Austin	1,701			6,162	567	138	227
Bailey	2,148			31,848	278	23,748	235
Bandera	2,064			119	382	206	200
Bastrop	2,320			3,306	533	181	191
Baylor	2,332			2,905	323	38,994	216
Bee	2,279			33,091	465	965	175
Bell	2,817			44,439	596	19,604	298
Bexar	3,253			16,674	432	6,397	232
Blanco	1,847			106	382	184	200
Borden	2,348			2,947	331	979	210
Bosque	2,596			2,405	371	5,390	230
Bowie	2,404			5,803	551	4,974	326
Brazoria	3,856			29,517	666	2,156	280
Brazos	1,529			8,422	605	722	297
Brewster	16,094			710	499	360	294
Briscoe	2,335			14,022	365	11,009	164
Brooks	2,442			1,950	278	62	185
Brown	2,476			739	381	3,272	182
Burleson	1,756			9,666	531	1,122	273
Burnet	2,643			152	382	263	216
Caldwell	1,417			14,767	550	703	237
Calhoun	1,065			19,085	598		
Callahan	2,332			1,725	388	10,899	211
Cameron	2,481			178,835	487	52	138
Camp	528			46	470	8	264
Carson	2,394			58,295	352	60,618	233
Cass	2,498			219	470	35	264
Castro	2,333			42,259	489	102,582	354
Chambers	1,649			8,948	698	944	259
Cherokee	2,758			242	470	39	264
Childress	1,848			2,443	389	15,890	161
Clay	2,886			586	364	20,027	228
Cochran	2,013			34,538	248	6,621	186
Coke	2,403			1,736	357	2,085	129
Coleman	3,317			4,608	206	21,395	178
Collin	2,295			31,521	617	52,601	351
Collingsworth	2,380			2,347	414	7,475	199
Colorado	2,524			3,542	491	673	222
Comal	1,487			2,025	492	1,272	227
Comanche	2,453	229	152	2,540	369	2,184	272
Concho	2,572			7,970	308	21,745	179
Cooke	2,323			19,251	513	30,750	336
Coryell	2,736			12,307	476	13,160	271
Cottle	2,334			1,318	362	4,499	153
Crane	2,039			412	499	209	294
Crockett	7,277			419	382	477	200
Crosby	2,336			24,052	283	6,145	135
Culberson	9,936			438	499	1,550	348
Dallam	3,906			26,329	399	129,137	364
Dallas	2,354			3,061	564	6,052	329
Dawson	2,339			20,644	224	2,927	220
Deaf Smith	3,887			84,882	377	102,368	251
Delta	721			3,568	551	13,340	371
Denton	2,481			26,485	479	28,807	252
DeWitt	2,358			3,129	464	191	227
Dickens	2,344			3,530	352	4,406	144
Dimmit	3,454			514	275	821	225
Donley	2,416			2,556	354	5,642	234
Duval	4,648			14,499	296	525	130
Eastland	2,412			1,559	406	2,714	200
Ector	2,340			473	499	240	294
Edwards	5,489			316	382	722	198
El Paso	2,656			1,704	526	521	276
Ellis	2,465			39,537	656	37,731	308
Erath	2,820			1,342	332	721	254
Falls	2,005			14,397	513	12,295	312
Fannin	2,332			14,258	512	42,692	307
Fayette	2,486			3,140	517	202	227
Fisher	2,335			3,424	251	6,968	161
Floyd	2,572			86,816	472	31,299	174
Foard	1,832			8,632	347	37,932	222
Fort Bend	2,299			64,934	594	886	199
Franklin	765			67	470	329	305
Freestone	2,313			1,320	596	64	227
Frio	2,935			10,403	411	5,576	230
Gaines	3,900	3,263	176	11,884	202	26,807	254
Galveston	1,065			2,781	573	258	224

Garza	2,322			6,880	378	1,223	169
Gillespie	2,747			2,727	396	3,518	222
Glasscock	2,335			6,395	190	4,547	149
Goliad	2,225			2,049	431	180	227
Gonzales	2,770			4,525	601	225	227
Gray	2,406			27,229	369	26,577	202
Grayson	2,536			28,215	558	43,225	348
Gregg	718			63	470	10	264
Grimes	2,078			2,283	627	58	227
Guadalupe	1,849			41,857	475	9,631	253
Hale	2,605			82,256	501	28,771	262
Hall	2,341			2,331	303	2,298	171
Hamilton	2,165			4,983	437	3,797	251
Hansford	2,384			47,563	368	133,038	263
Hardeman	1,803			2,291	365	37,190	189
Hardin	2,334			1,881	404	1,248	280
Harris	4,607			1,784	490	1,115	224
Harrison	2,379	34	113	208	470	34	264
Hartley	3,796			32,068	493	92,743	374
Haskell	2,356			9,811	314	73,274	189
Hays	1,759			4,549	447	1,576	218
Hemphill	2,361			1,490	356	5,494	185
Henderson	2,461			216	470	509	314
Hidalgo	4,099			226,414	404	86	138
Hill	2,553			115,160	643	52,475	349
Hockley	2,357			47,654	294	3,751	215
Hood	1,131			229	364	401	283
Hopkins	2,056	181	172	1,607	496	686	283
Houston	3,209			281	470	279	230
Howard	2,343			4,719	179	1,445	191
Hudspeth	11,938			804	248	1,412	349
Hunt	2,287			16,738	512	25,548	342
Hutchinson	2,319			14,440	407	40,787	224
Irion	2,724			157	382	394	146
Jack	2,382			483	364	627	198
Jackson	2,221			65,079	612	517	232
Jasper	2,524			418	596	70	227
Jeff Davis	5,894			260	499	132	294
Jefferson	2,576			2,025	400	992	224
Jim Hogg	2,941			437	275	74	185
Jim Wells	2,248			65,132	331	963	204
Johnson	1,902			15,501	489	12,027	320
Jones	2,426			9,076	279	48,194	165
Karnes	1,951			6,756	419	3,239	223
Kaufman	2,091			4,608	589	8,613	345
Kendall	1,716			99	382	171	200
Kenedy	3,568			3,155	275	90	185
Kent	2,338			1,125	293	2,427	160
Kerr	2,867			165	382	286	200
Kimble	3,238			186	382	212	174
King	2,364			2,336	309	2,999	170
Kinney	3,535			203	382	335	197
Kleberg	2,277			71,980	460	821	254
Knox	2,214			2,349	272	89,192	216
La Salle	3,867			1,652	319	848	225
Lamar	2,417			9,221	613	25,341	378
Lamb	2,640			75,691	442	18,210	275
Lampasas	1,848			1,543	424	1,171	217
Lavaca	2,513			1,881	531	204	227
Lee	1,643			1,580	464	133	227
Leon	2,802			1,599	596	78	227
Liberty	3,056			19,278	586	1,642	169
Limestone	2,418			5,491	547	2,243	262
Lipscomb	2,413			10,834	382	19,064	228
Live Oak	2,792			7,491	390	480	132
Llano	2,501			144	382	1,051	216
Loving	1,760			356	499	181	294
Lubbock	2,335			43,854	304	5,953	192
Lynn	2,316			17,012	235	2,358	183
Madison	1,225			699	596	34	227
Marion	1,093			96	470	16	264
Martin	2,374			18,799	231	1,926	184
Mason	2,412			139	382	1,036	236
Matagorda	3,144			82,819	636	1,373	224
Maverick	3,346			498	275	84	185
McCulloch	2,778			1,588	344	27,631	225
McLennan	2,746	272	326	42,645	594	38,057	331
McMullen	2,958			1,053	297	657	135
Medina	3,453			40,326	468	13,187	235
Menard	2,336			134	382	1,295	186
Midland	2,339			2,945	206	1,228	143
Milam	2,647			29,641	622	6,156	294
Mills	1,941			948	426	1,321	207
Mitchell	2,372			1,918	195	3,923	186
Montague	2,426			492	364	4,126	273
Montgomery	2,795			463	596	78	227
Moore	2,358			53,741	497	90,166	298
Morris	672			59	470	10	264

Motley	2,563			568	301	1,327	157
Nacogdoches	2,550			223	470	36	264
Navarro	2,815			31,757	559	7,683	278
Newton	2,452			406	596	68	227
Nolan	2,366			3,777	253	5,992	170
Nueces	2,175			310,508	473	161	210
Ochiltree	2,377			81,442	437	114,335	239
Oldham	3,896			9,516	275	15,420	193
Orange	988			2,642	552	381	224
Palo Pinto	2,551			518	364	949	227
Panola	2,137			187	470	30	264
Parker	2,356			478	364	389	206
Parmer	2,298			82,074	550	104,086	298
Pecos	12,370			1,318	407	1,984	207
Polk	2,883			477	596	80	227
Potter	2,390			5,600	328	9,056	197
Presidio	10,045			443	499	225	294
Rains	672			59	470	378	287
Randall	2,391			24,358	356	32,749	190
Reagan	3,047			1,157	265	2,562	165
Real	1,812			104	382	181	200
Red River	2,752			6,060	499	2,003	316
Reeves	6,870			1,114	459	2,143	297
Refugio	2,119			56,414	542	157	210
Roberts	2,394			4,002	332	7,655	207
Robertson	2,244			5,878	573	372	230
Rockwall	385			10,963	635	6,096	364
Runnels	2,736			23,195	312	50,730	188
Rusk	2,438			214	470	35	264
Sabine	1,490			247	596	41	227
San Augustine	1,541			255	596	43	227
San Jacinto	1,630			270	596	45	227
San Patricio	1,830			204,114	554	136	210
San Saba	2,946			1,447	511	9,754	272
Schleicher	3,393			2,406	336	3,264	161
Scurry	2,351			2,730	197	4,049	169
Shackelford	2,370			1,447	596	9,412	190
Shelby	2,166			190	470	31	264
Sherman	2,393			47,504	535	154,942	361
Smith	2,464			216	470	35	264
Somervell	497			101	364	779	206
Starr	3,181			42,645	266	67	138
Stephens	2,384			484	364	1,223	168
Sterling	2,392			868	429	1,152	184
Stonewall	2,383			1,061	218	13,564	193
Sutton	3,766			217	382	302	155
Swisher	2,335			45,666	411	54,894	236
Tarrant	2,324			5,385	605	4,596	245
Taylor	2,379			5,928	287	41,614	206
Terrell	6,117			270	499	137	294
Terry	2,311			16,347	251	7,124	223
Throckmorton	2,369			2,074	427	28,353	226
Titus	1,105			97	470	16	264
Tom Green	3,989			33,481	334	24,016	212
Travis	2,646			26,897	507	2,867	227
Trinity	1,854			307	596		
Tyler	2,432			403	596	68	227
Upshur	1,540			135	470	22	264
Upton	3,221			1,784	315	3,108	165
Uvalde	4,035			25,590	541	13,494	239
Val Verde	8,390			483	382	550	200
Van Zandt	2,228			195	470	368	284
Victoria	2,301			38,385	602	361	149
Walker	2,080	24	186	2,390	554	58	227
Waller	1,345			1,897	521	37	227
Ward	2,173			439	499	223	294
Washington	1,611			1,549	464	1,116	221
Webb	8,740			1,300	275	221	185
Wharton	2,837			148,064	641	489	161
Wheeler	2,370	2,074	155	2,009	289	4,823	165
Wichita	1,638			2,096	227	63,292	240
Wilbarger	2,532			5,219	280	86,144	235
Willacy	1,548			168,108	453	33	138
Williamson	2,937			74,407	567	7,677	250
Wilson	2,093			26,726	523	2,336	195
Winkler	2,185			442	499	591	365
Wise	2,389	5	378	2,419	443	3,020	233
Wood	1,806			158	470	306	284
Yoakum	2,077			14,879	243	11,064	274
Young	2,409			1,826	403	18,309	199
Zapata	2,738			407	275	69	185
Zavala	3,369			11,027	529	8,618	199

Other Field Crops

County	Area (Km^2)	Beans		Cotton (Pima)		Cotton (Upland)		Cow Peas		Guar		Pea	
		P	NPP	P	NPP	P	NPP	P	NPP	P	NPP	P	NPP
Anderson	2,797	5	42			310	55	5	27			3	13
Andrews	3,896					5,534	80						
Angelina	2,247					28	88						
Aransas	741					507	84						
Archer	2,396					20	47						
Armstrong	2,368					556	102						
Atascosa	3,198					1,718	135						
Austin	1,701					1,216	97						
Bailey	2,148	234	40			18,734	79						
Bandera	2,064					15	101						
Bastrop	2,320					118	94						
Baylor	2,332					1,277	73						
Bee	2,279					6,093	98						
Bell	2,817					1,065	84						
Bexar	3,253					1,089	168						
Blanco	1,847					13	101						
Borden	2,348					4,286	65						
Bosque	2,596					88	69						
Bowie	2,404					13	71						
Brazoria	3,856					2,314	93						
Brazos	1,529					4,666	126						
Brewster	16,094			52	101	174	133						
Briscoe	2,335					7,544	68						
Brooks	2,442					282	63						
Brown	2,476					84	35						
Burleson	1,756					5,750	126						
Burnet	2,643					19	101						
Caldwell	1,417					1,127	80						
Calhoun	1,065					9,083	98						
Callahan	2,332					19	47						
Cameron	2,481					16,509	85						
Camp	528					3	71						
Carson	2,394					7,140	113						
Cass	2,498					13	71						
Castro	2,333	98	53			37,995	134						
Chambers	1,649							9	73				
Cherokee	2,758					15	71					14	66
Childress	1,848					9,069	59						
Clay	2,886					169	33						
Cochran	2,013					32,296	80						
Coke	2,403					214	63						
Coleman	3,317					695	47						
Collin	2,295					518	64						
Collingsworth	2,380					12,200	84						
Colorado	2,524					1,385	83						
Comal	1,487					76	94						
Comanche	2,453					20	47						
Concho	2,572					4,474	52						
Cooke	2,323					79	69						
Coryell	2,736					93	69						
Cottle	2,334					3,061	47						
Crane	2,039			7	101	80	133						
Crockett	7,277					51	101						
Crosby	2,336					55,691	72						
Culberson	9,936			32	101	746	142						
Dallam	3,906					141	58						
Dallas	2,354					80	69						
Dawson	2,339					59,860	75						
Deaf Smith	3,887	253	52			12,871	109						
Delta	721					300	66						
Denton	2,481					85	69						
DeWitt	2,358					120	94						
Dickens	2,344					4,628	53						
Dimmit	3,454					873	127						
Donley	2,416					3,277	76						
Duval	4,648	229	25			197	61						
Eastland	2,412					20	47						
Ector	2,340			8	101	92	133						
Edwards	5,489					39	101						
El Paso	2,656			9,017	143	4,455	183						
Ellis	2,465					8,008	71						
Erath	2,820					23	47						
Falls	2,005					1,436	83						
Fannin	2,332					310	70						
Fayette	2,486					126	94						
Fisher	2,335					12,214	56						
Floyd	2,572					48,782	87						
Foard	1,832					1,145	32						
Fort Bend	2,299	8	106			17,749	86						
Franklin	765					4	71	2	22				

Freestone	2,313					29	88					
Frio	2,935	235	69			1,781	153					
Gaines	3,900					79,810	94					
Galveston	1,065											
Garza	2,322					9,684	66					
Gillespie	2,747					19	101					
Glasscock	2,335					18,640	73					
Goliad	2,225					596	89					
Gonzales	2,770					141	94					
Gray	2,406					2,929	102					
Grayson	2,536					620	128					
Gregg	718					4	71					
Grimes	2,078	36	42			26	88					
Guadalupe	1,849					94	94					
Hale	2,605					104,957	110					
Hall	2,341					17,016	59					
Hamilton	2,165					74	69					
Hansford	2,384					2,648	152					
Hardeman	1,803					1,948	75					
Hardin	2,334					29	88					
Harris	4,607											
Harrison	2,379					13	71					
Hartley	3,796	434	55			1,431	100					
Haskell	2,356					19,007	61			1,556	105	
Hays	1,759					521	92					
Hemphill	2,361					221	100					
Henderson	2,461					13	71					
Hidalgo	4,099					21,537	104					
Hill	2,553					5,168	76					
Hockley	2,357					64,892	77			416	113	
Hood	1,131					9	47					
Hopkins	2,056					11	71	15	36			
Houston	3,209					803	78	45	46			
Howard	2,343					15,453	51					
Hudspeth	11,938			1,798	146	3,943	163					
Hunt	2,287					685	56	3	28			
Hutchinson	2,319					1,239	128					
Irion	2,724					84	26					
Jack	2,382					19	47					
Jackson	2,221					12,904	90					
Jasper	2,524					31	88					
Jeff Davis	5,894			19	101	64	133					
Jefferson	2,576											
Jim Hogg	2,941					134	99					
Jim Wells	2,248					3,896	83					
Johnson	1,902					65	69					
Jones	2,426					12,158	49					
Karnes	1,951					760	87					
Kaufman	2,091					71	69					
Kendall	1,716					12	101					
Kenedy	3,568					807	99					
Kent	2,338					545	50					
Kerr	2,867					20	101					
Kimble	3,238					23	101					
King	2,364					385	52					
Kinney	3,535					563	116					
Kleberg	2,277					11,283	83					
Knox	2,214					11,435	101			843	117	
La Salle	3,867					479	118					
Lamar	2,417					549	70	3	28			
Lamb	2,640	448	75			70,159	104					
Lampasas	1,848					13	101					
Lavaca	2,513					128	94					
Lee	1,643					83	94					
Leon	2,802					35	88					
Liberty	3,056	7	47									
Limestone	2,418					737	60	20	86			
Lipscomb	2,413					225	100					
Live Oak	2,792					1,051	85					
Llano	2,501					18	101					
Loving	1,760			6	101	69	133					
Lubbock	2,335	195	29			75,477	81					
Lynn	2,316					64,258	64					
Madison	1,225					15	88					
Marion	1,093					6	71					
Martin	2,374					20,959	59			320	48	
Mason	2,412					17	101					
Matagorda	3,144					13,374	107					
Maverick	3,346					152	99					
McCulloch	2,778					775	43					
McLennan	2,746					1,742	85					
McMullen	2,958					807	99					
Medina	3,453					4,868	166					
Menard	2,336					16	101					
Midland	2,339					4,661	53					

Milam	2,647					3,117	92	57	73				
Mills	1,941					16	47						
Mitchell	2,372					9,764	55						
Montague	2,426					20	47						
Montgomery	2,795	0	30			35	88						
Moore	2,358	73	34			7,004	145						
Morris	672					4	71						
Motley	2,563					4,014	43						
Nacogdoches	2,550	10	50			13	71	5	17				
Navarro	2,815					4,535	71						
Newton	2,452					31	88						
Nolan	2,366					9,168	51						
Nueces	2,175					48,455	97						
Ochiltree	2,377					2,169	120						
Oldham	3,896					446	100						
Orange	988												
Palo Pinto	2,551					21	47						
Panola	2,137					11	71	20	43				
Parker	2,356	0	35			19	47						
Parmer	2,298	1,236	59			37,919	140	77	46				
Pecos	12,370			40	101	3,680	139						
Polk	2,883					36	88						
Potter	2,390					324	80						
Presidio	10,045			33	101	109	133						
Rains	672					4	71						
Randall	2,391					892	95						
Reagan	3,047					6,220	90						
Real	1,812					13	101						
Red River	2,752					1,164	81						
Reeves	6,870			22	101	1,718	120						
Refugio	2,119					16,012	101						
Roberts	2,394					648	123						
Robertson	2,244					9,726	118						
Rockwall	385					13	69						
Runnels	2,736					9,346	53						
Rusk	2,438	8	38			13	71						
Sabine	1,490					19	88						
San Augustine	1,541					19	88						
San Jacinto	1,630					20	88						
San Patricio	1,830					55,837	110						
San Saba	2,946					21	101						
Schleicher	3,393					1,211	48						
Scurry	2,351					9,877	49						
Shackelford	2,370					329	54						
Shelby	2,166					11	71						
Sherman	2,393					3,901	144						
Smith	2,464					13	71					1	85
Somervell	497					4	47						
Starr	3,181					995	94						
Stephens	2,384	43	32			19	47						
Sterling	2,392					394	101						
Stonewall	2,383					962	45						
Sutton	3,766					27	101						
Swisher	2,335					28,019	101						
Tarrant	2,324					79	69						
Taylor	2,379					2,652	53						
Terrell	6,117			20	101	66	133						
Terry	2,311	258	32			62,991	73	149	56	1,442	109		
Throckmorton	2,369					437	52						
Titus	1,105					6	71						
Tom Green	3,989					17,908	66						
Travis	2,646					784	64						
Trinity	1,854					23	88						
Tyler	2,432	2	70			30	88	2	42				
Upshur	1,540					8	71						
Upton	3,221					2,807	82						
Uvalde	4,035					5,919	146						
Val Verde	8,390					59	101						
Van Zandt	2,228					12	71						
Victoria	2,301					5,525	88						
Walker	2,080					377	78						
Waller	1,345					17	88						
Ward	2,173			7	101	86	133						
Washington	1,611					82	94						
Webb	8,740					397	99						
Wharton	2,837					29,296	98						
Wheeler	2,370					2,239	74						
Wichita	1,638					1,371	39						
Wilbarger	2,532					4,323	47			1,003	67		
Willacy	1,548					21,560	88						
Williamson	2,937	6	88			7,267	79						
Wilson	2,093					1,098	141						
Winkler	2,185			7	101	86	133						
Wise	2,389					20	47						

Wood	1,806			10	71				9	212
Yoakum	2,077			31,775	84	134	70			
Young	2,409			197	42					
Zapata	2,738			124	99					
Zavala	3,369			2,446	135					

Other Field Crops (continued)

County	Area (Km^2)	Peanut		Potato		Soybean		Sugarcane		Sunflower		Sweet Potato	
		P	NPP	P	NPP	P	NPP	P	NPP	P	NPP	P	NPP
Anderson	2,797	22	107			44	190						
Andrews	3,896	12,022	534			191	224			304	168		
Angelina	2,247	18	234			34	204						
Aransas	741									82	129		
Archer	2,396	145	194										
Armstrong	2,368	73	424			1,425	252			386	165		
Atascosa	3,198	12,036	396							98	162		
Austin	1,701	56	217			58	182			33	184		
Bailey	2,148	3,395	373			2,497	301			2,057	154		
Bandera	2,064	17	414							5	192		
Bastrop	2,320	76	217			80	182			45	184		
Baylor	2,332	386	302										
Bee	2,279	75	217			78	182			44	184		
Bell	2,817	90	269	4	968	258	172						
Bexar	3,253	107	217			112	182			62	184		
Blanco	1,847	15	414							4	192		
Borden	2,348	214	281			53	222						
Bosque	2,596	83	269			238	172						
Bowie	2,404	19	107			6,318	206						
Brazoria	3,856			124	160	2,606	207						
Brazos	1,529	12	234			633	174						
Brewster	16,094												
Briscoe	2,335	2,716	419			4,387	327			380	165		
Brooks	2,442	95	424							75	162		
Brown	2,476	915	206										
Burleson	1,756	58	217			2,816	243			34	184		
Burnet	2,643	22	414							6	192		
Caldwell	1,417	47	217			49	182			27	184		
Calhoun	1,065					4,414	202						
Callahan	2,332	142	194										
Cameron	2,481	501	513			293	213	46,977	650	6,973	239		
Camp	528	4	107			8	190						
Carson	2,394	74	424			6,087	298			2,054	129		
Cass	2,498	20	107			39	190						
Castro	2,333	72	424			2,299	278			482	132		
Chambers	1,649					1,354	164						
Cherokee	2,758	22	107			43	190						
Childress	1,848	2,685	326			42	222						
Clay	2,886	175	194										
Cochran	2,013	12,393	389			1,853	241			854	120		
Coke	2,403	20	414							5	192		
Coleman	3,317	123	302										
Collin	2,295	73	269			822	119						
Collingsworth	2,380	33,779	301			54	222						
Colorado	2,524	83	217			1,578	192			48	184		
Comal	1,487	49	217			51	182			29	184		
Comanche	2,453	4,460	238										
Concho	2,572	21	414							6	192		
Cooke	2,323	1,524	269	38	4,712	602	172						
Coryell	2,736	87	269			251	172						
Cottle	2,334	1,937	270			53	222						
Crane	2,039												
Crockett	7,277	60	414							16	192		
Crosby	2,336	1,275	315			1,425	252			1,136	109		
Culberson	9,936												
Dallam	3,906	120	424	4,337	1,022	2,819	321			3,332	206		
Dallas	2,354	75	269			4,832	244						
Dawson	2,339	25,836	505			115	224			972	136		
Deaf Smith	3,887	120	424			3,729	272			548	150		
Delta	721	23	269			6,578	163						
Denton	2,481	468	139	2	290	190	94						
DeWitt	2,358	78	217			81	182			45	184		
Dickens	2,344	214	281			53	222						
Dimmit	3,454	134	424							106	162		
Donley	2,416	10,404	491			55	222						
Duval	4,648	181	424							142	162		
Eastland	2,412	3,080	232										
Ector	2,340												
Edwards	5,489	46	414							12	192		
El Paso	2,656												
Ellis	2,465	79	269			5,065	232						
Erath	2,820	1,622	219										
Falls	2,005	64	269	51	976	4,153	210						
Fannin	2,332	775	120			9,614	173						
Fayette	2,486	82	217			85	182			48	184		
Fisher	2,335	87	302										
Floyd	2,572	79	424			3,642	297			1,739	162		
Foard	1,832	167	281			42	222						
Fort Bend	2,299					3,085	188						
Franklin	765	6	107			12	190						

Freestone	2,313	18	234	19	526	35	204					
Frio	2,935	23,874	465	14,767	501					90	162		
Gaines	3,900	147,552	543	3,154	728	633	261			305	168		
Galveston	1,065					713	163						
Garza	2,322	212	281			53	222						
Gillespie	2,747	23	414							6	192	9	308
Glasscock	2,335	759	462			115	224			182	168		
Goliad	2,225	73	217			697	172			43	184		
Gonzales	2,770	91	217			95	182			53	184	1	20
Gray	2,406	74	424			2,171	301			1,089	80		
Grayson	2,536	806	176			908	164						
Gregg	718	6	107			11	190						
Grimes	2,078	17	234			31	204						
Guadalupe	1,849	61	217	3	318	63	182			35	184		
Hale	2,605	80	424			5,855	257			2,210	202		
Hall	2,341	7,246	285			53	222						
Hamilton	2,165	69	269			198	172						
Hansford	2,384	73	424			6,810	341			2,306	201		
Hardeman	1,803	165	281			41	222						
Hardin	2,334	19	234	2	118	35	204						
Harris	4,607	354	146	4	971	665	164						
Harrison	2,379	19	107			37	190						
Hartley	3,796	117	424			2,056	339			3,933	266		
Haskell	2,356	14,224	443										
Hays	1,759	58	217			60	182			34	184		
Hemphill	2,361	73	424			4,387	327			727	165		
Henderson	2,461	20	107			39	190					47	552
Hidalgo	4,099	828	513			1,679	244	57,490	706	6,710	185		
Hill	2,553	82	269			234	172						
Hockley	2,357	15,139	445			116	224			1,167	120		
Hood	1,131	69	194										
Hopkins	2,056	16	107	0	19	1,267	229						
Houston	3,209	25	107			51	190						
Howard	2,343	761	462			115	224			183	168		
Hudspeth	11,938												
Hunt	2,287	73	269			5,983	181						
Hutchinson	2,319	71	424			1,964	303			715	165		
Irion	2,724	23	414							6	192		
Jack	2,382	145	194										
Jackson	2,221					6,504	197						
Jasper	2,524	20	234	31	1,092	38	204						
Jeff Davis	5,894												
Jefferson	2,576					744	194						
Jim Hogg	2,941	114	424							90	162		
Jim Wells	2,248	87	424							3,844	150		
Johnson	1,902	61	269			174	172						
Jones	2,426	90	302										
Karnes	1,951	64	217			67	182			37	184		
Kaufman	2,091	67	269			1,464	174						
Kendall	1,716	14	414							4	192		
Kenedy	3,568	139	424							109	162		
Kent	2,338	213	281			53	222						
Kerr	2,867	24	414							6	192		
Kimble	3,238	27	414							7	192		
King	2,364	216	281			54	222						
Kinney	3,535	29	414							8	192		
Kleberg	2,277									615	152		
Knox	2,214	367	302										
La Salle	3,867	150	424							118	162		
Lamar	2,417	77	269			13,563	167						
Lamb	2,640	9,081	467			4,441	264			3,416	156		
Lampasas	1,848	15	414							4	192		
Lavaca	2,513	83	217			86	182			48	184		
Lee	1,643	860	152			56	182			32	184		
Leon	2,802	22	234			42	204						
Liberty	3,056					4,155	155						
Limestone	2,418	77	269	14	429	221	172						
Lipscomb	2,413	74	424			760	235			908	160		
Live Oak	2,792	108	424							85	162		
Llano	2,501	21	414							6	192		
Loving	1,760												
Lubbock	2,335	4,527	339			958	225			2,219	106		
Lynn	2,316	2,180	425			114	224			980	128		
Madison	1,225	10	234			19	204						
Marion	1,093	9	107			17	190						
Martin	2,374	771	462			116	224			185	168		
Mason	2,412	2,953	561							5	192		
Matagorda	3,144					9,814	228						
Maverick	3,346	130	424							102	162		
McCulloch	2,778	23	414							6	192		
McLennan	2,746	88	269			1,801	178						
McMullen	2,958	115	424							90	162		
Medina	3,453	114	217			119	182			1,185	163		
Menard	2,336	19	414							5	192		
Midland	2,339	760	462			115	224			183	168		

Milam	2,647	85	269			242	172						
Mills	1,941	1,587	194										
Mitchell	2,372	88	302										
Montague	2,426	147	194										
Montgomery	2,795	22	234	23	1,122	42	204						
Moore	2,358	73	424			3,566	308			6,642	205		
Morris	672	5	107			11	190						
Motley	2,563	2,905	326			58	222						
Nacogdoches	2,550	20	107	8	43	40	190						
Navarro	2,815	90	269			1,837	239						
Newton	2,452	20	234			37	204						
Nolan	2,366	88	302										
Nueces	2,175									1,394	144		
Ochiltree	2,377	73	424			11,070	361			2,283	158		
Oldham	3,896	120	424			1,970	327			635	165		
Orange	988					713	163						
Palo Pinto	2,551	155	194										
Panola	2,137	17	107			34	190						
Parker	2,356	130	81										
Parmer	2,298	71	424			2,823	247			1,276	194		
Pecos	12,370												
Polk	2,883	23	234			44	204						
Potter	2,390	74	424			1,208	327			389	165		
Presidio	10,045												
Rains	672	5	107			11	190						
Randall	2,391	74	424			1,209	327			389	165		
Reagan	3,047	25	414							7	192		
Real	1,812	15	414							4	192		
Red River	2,752	22	107			5,880	211						
Reeves	6,870												
Refugio	2,119									235	129		
Roberts	2,394	74	424			1,428	294			737	165		
Robertson	2,244	18	234	1	70	3,288	260						
Rockwall	385	12	269			2,298	172						
Runnels	2,736	102	302										
Rusk	2,438	19	107			38	190						
Sabine	1,490	12	234			23	204						
San Augustine	1,541	12	234			23	204						
San Jacinto	1,630	13	234			25	204						
San Patricio	1,830									203	129		
San Saba	2,946	24	414							7	192		
Schleicher	3,393	28	414							8	192		
Scurry	2,351	87	302										
Shackelford	2,370	144	194										
Shelby	2,166	17	107			34	190						
Sherman	2,393	74	424			4,171	339			5,270	234		
Smith	2,464	20	107	81	1,331	39	190					5	107
Somervell	497	30	194										
Starr	3,181	642	513			475	213			2,035	136		
Stephens	2,384	145	194										
Sterling	2,392	20	414							5	192		
Stonewall	2,383	590	151										
Sutton	3,766	31	414							9	192		
Swisher	2,335	72	424			1,499	242			2,117	174		
Tarrant	2,324	74	269			213	172						
Taylor	2,379	88	302										
Terrell	6,117												
Terry	2,311	59,403	492			113	224			181	168		
Throckmorton	2,369	144	194										
Titus	1,105	9	107			17	190						
Tom Green	3,989	33	414							9	192		
Travis	2,646	87	217			91	182			51	184		
Trinity	1,854	15	234			28	204						
Tyler	2,432	19	234	492	2,825	37	204						
Upshur	1,540	12	107			24	190						
Upton	3,221	27	414							7	192		
Uvalde	4,035	33	414							783	194		
Val Verde	8,390	70	414							19	192		
Van Zandt	2,228	18	107	50	942	35	190					1,587	351
Victoria	2,301					13,129	214						
Walker	2,080	17	234			31	204						
Waller	1,345	1,274	246			20	204						
Ward	2,173												
Washington	1,611	53	217			55	182			31	184		
Webb	8,740	340	424							267	162		
Wharton	2,837					14,630	224						
Wheeler	2,370	2,958	237			54	222						
Wichita	1,638	1,401	281			412	145						
Wilbarger	2,532	4,626	429			1,191	142						
Willacy	1,548	313	513			183	213	16,683	773	857	145		
Williamson	2,937	94	269			269	172						
Wilson	2,093	4,060	312			72	182			40	184		
Winkler	2,185												
Wise	2,389	965	281	12	725								

Wood	1,806	14	107	29	478	28	190					677	363
Yoakum	2,077	42,603	473			102	224			1,238	90		
Young	2,409	146	194										
Zapata	2,738	106	424							84	162		
Zavala	3,369	131	424							103	162		

Hay and Silage

County	Area (Km²)	Bahia Grass Seed		Corn for Silage		Hay		Haylage		Other Seed		Rye Grass Seed		Sorghum for Silage	
		P	NPP	P	NPP	P	NPP	P	NPP	P	NPP	P	NPP	P	NPP
Anderson	2,797	7	12	280	558	84,774	30	362	136						
Andrews	3,896			4,226	966	1,059	0								
Angelina	2,247	2	8	109	478										
Aransas	741					524	1								
Archer	2,396			1,070	596	38,419	16	6,877	336					537	453
Armstrong	2,368			9,867	1,006	7,402	3	323	246						
Atascosa	3,198			81	332	34,833	11	865	396						
Austin	1,701			305	625	71,568	42	337	185						
Bailey	2,148			2,329	966	17,952	8	504	308						
Bandera	2,064			85	522	8,245	4	87	92					665	629
Bastrop	2,320			416	625	52,388	23	400	117						
Baylor	2,332					10,516	5							363	97
Bee	2,279			409	625	18,632	8	293	127						
Bell	2,817			3,117	499	44,727	16	284	210					371	367
Bexar	3,253			583	625	46,416	14	358	174					722	373
Blanco	1,847			76	522	8,604	5	155	524						
Borden	2,348			320	927	1,469	1								
Bosque	2,596			2,872	499	53,820	21	198	123					427	233
Bowie	2,404			241	558	56,462	23	898	198						
Brazoria	3,856					45,086	12	65	51						
Brazos	1,529			74	478										
Brewster	16,094			1,269	348										
Briscoe	2,335			9,733	1,006	8,793	4	86	79						
Brooks	2,442			62	332	4,163	2	23	47						
Brown	2,476			1,106	596	39,815	16	1,458	248					3,293	379
Burleson	1,756			315	625										
Burnet	2,643			109	522	15,095	6	191	344					13	107
Caldwell	1,417			254	625	33,434	24	46	61						
Callahan	2,332			1,042	596	20,377	9	180	97					200	192
Cameron	2,481			737	623	15,085	6	180	155					2,011	183
Camp	528			53	558										
Carson	2,394			9,976	1,006	17,157	7	583	406					370	474
Cass	2,498	33	22	250	558	39,320	16	247	220						
Castro	2,333			9,721	1,006	36,142	15	799	191					19,993	859
Chambers	1,649	1	4			24,959	15	133	171						
Cherokee	2,758			276	558	72,117	26	920	146						
Childress	1,848			252	927										
Clay	2,886			1,289	596	38,347	13	2,601	289					313	271
Cochran	2,013			2,183	966									7,376	631
Coke	2,403			99	522										
Coleman	3,317					25,410	8	464	80					2,392	521
Collin	2,295			2,540	499	47,374	21	865	183						
Collingsworth	2,380			324	927										
Colorado	2,524	4	7	453	625	45,456	18	53	70						
Comal	1,487			267	625	11,173	8	63	79						
Comanche	2,453			1,096	596	107,244	44	4,420	370					10,480	530
Concho	2,572			106	522										
Cooke	2,323			2,570	499	82,489	36	2,846	243					1,860	576
Coryell	2,736			3,027	499	36,481	13	1,127	202						
Cottle	2,334			318	927										
Crane	2,039			161	348	82	0								
Crockett	7,277			299	522										
Crosby	2,336			2,534	966										
Culberson	9,936			783	348	5,487	1								
Dallam	3,906			16,280	1,006									1,565	1,074
Dallas	2,354			2,604	499	15,726	7	213	176						
Dawson	2,339			2,537	966										
Deaf Smith	3,887			16,200	1,006	21,441	6	2,751	300					13,581	737
Delta	721			798	499	22,986	32	10	39						
Denton	2,481			2,745	499	65,236	26	565	121					349	114
DeWitt	2,358			423	625	52,890	22	41	72					273	373
Dickens	2,344			319	927	12,370	5	198	202					72	282
Dimmit	3,454			87	332	2,238	1								
Donley	2,416			329	927	16,477	7	205	155						
Duval	4,648			117	332	15,628	3	1,225	455					53	116
Eastland	2,412			1,077	596	67,198	28	1,027	224					308	264
Ector	2,340			184	348										
Edwards	5,489			226	522										
El Paso	2,656			209	348	16,827	6	618	514						
Ellis	2,465			2,727	499	67,202	27	1,233	161					1,547	332
Erath	2,820			1,260	596	110,199	39	20,883	409					17,535	563
Falls	2,005			2,218	499	48,042	24	130	141						
Fannin	2,332			2,580	499	92,465	40	3,624	283					56	344
Fayette	2,486			446	625	104,361	42	212	88						
Fisher	2,335					11,806	5	1,075	401					508	190
Floyd	2,572			10,718	1,006									3,401	869
Foard	1,832			250	927	12,355	7	44	43						
Fort Bend	2,299					30,112	13	177	368					130	518
Franklin	765			77	558	36,037	47	1,632	451						

Freestone	2,313			112	478									
Frio	2,935			74	332									
Gaines	3,900			4,230	966	30,472	8	174	82				2,909	606
Galveston	1,065					5,720	5							
Garza	2,322			316	927									
Gillespie	2,747			113	522	25,902	9	337	149				392	188
Glasscock	2,335			2,533	966	5,466	2	746	550					
Goliad	2,225			399	625	21,879	10	226	399					
Gonzales	2,770			497	625	57,036	21	649	154					
Gray	2,406			10,028	1,006									
Grayson	2,536			2,806	499	77,457	31	418	165					
Gregg	718			72	558	7,703	11							
Grimes	2,078			101	478	58,785	28	301	124					
Guadalupe	1,849			332	625	58,652	32	611	130				1,207	579
Hale	2,605			10,854	1,006	16,609	6	808	364	60	19		2,785	605
Hall	2,341			319	927									
Hamilton	2,165			2,395	499	31,503	15	3,182	231				3,453	467
Hansford	2,384			9,935	1,006	10,265	4	1,218	367					
Hardeman	1,803			246	927	10,881	6	480	140					
Hardin	2,334	11	8	113	478									
Harris	4,607					42,288	9	52	102					
Harrison	2,379	0	3	238	558	38,515	16	223	431					
Hartley	3,796			15,820	1,006									
Haskell	2,356					12,394	5	127	82				279	127
Hays	1,759			316	625	11,095	6	99	107					
Hemphill	2,361			9,840	1,006	8,524	4	84	42				866	380
Henderson	2,461			247	558	104,361	42	393	135					
Hidalgo	4,099			1,219	623	34,930	9	104	41				2,319	272
Hill	2,553			2,824	499	62,820	25	1,679	290					
Hockley	2,357			2,556	966								6,180	555
Hood	1,131			505	596	37,505	33	883	176					
Hopkins	2,056			206	558	162,023	79	12,688	402				7,011	442
Houston	3,209	14	14	322	558	78,227	24	175	89					
Howard	2,343			2,541	966	9,746	4						462	509
Hudspeth	11,938			941	348									
Hunt	2,287			2,530	499	82,021	36	522	222				129	104
Hutchinson	2,319			9,666	1,006	3,272	1							
Irion	2,724			112	522	1,379	1	15	60					
Jack	2,382			1,064	596									
Jackson	2,221					20,044	9	74	160					
Jasper	2,524	6	13	123	478	20,940	8	206	129					
Jeff Davis	5,894			465	348	1,438	0							
Jefferson	2,576	2	3			27,027	10	53	262					
Jim Hogg	2,941			74	332	998	0							
Jim Wells	2,248			57	332	24,414	11	223	220				3,758	643
Johnson	1,902			2,104	499	82,728	43	5,346	344					
Jones	2,426					25,085	10	419	84				767	220
Karnes	1,951			350	625	38,079	20	2,873	733				807	317
Kaufman	2,091			2,314	499	90,252	43	159	132					
Kendall	1,716			71	522									
Kenedy	3,568			90	332									
Kent	2,338			319	927	3,594	2	9	41				403	682
Kerr	2,867			118	522	9,820	3	389	153					
Kimble	3,238			133	522									
King	2,364			322	927									
Kinney	3,535			145	522									
Kleberg	2,277					7,328	3							
La Salle	3,867			98	332	5,689	1							
Lamar	2,417			2,675	499	93,947	39	937	190					
Lamb	2,640			2,864	966	34,501	13	6,298	411				5,961	745
Lampasas	1,848			76	522	18,777	10	125	76				84	125
Lavaca	2,513			451	625	88,092	35	233	92				301	230
Lee	1,643			295	625	50,839	31	119	154					
Leon	2,802	1	4	136	478	90,301	32	193	63					
Liberty	3,056	3	17			47,413	16	622	172					
Limestone	2,418			2,675	499	61,070	25	470	224				900	660
Lipscomb	2,413			10,057	1,006									
Live Oak	2,792			71	332	32,819	12	91	132					
Llano	2,501			103	522	7,002	3	76	83					
Loving	1,760			139	348									
Lubbock	2,335			2,533	966	14,113	6	45	123	4	3		2,497	292
Lynn	2,316			2,512	966	5,424	2	135	157					
Madison	1,225	10	12	60	478	37,393	31	111	60					
Marion	1,093			110	558	10,331	9							
Martin	2,374			2,575	966									
Mason	2,412			99	522	13,755	6	104	286				1,478	629
Maverick	3,346			85	332									
McCulloch	2,778			114	522								340	208
McLennan	2,746			3,038	499	69,936	25	739	217				3,333	584
McMullen	2,958			75	332	3,020	1							
Medina	3,453			619	625	46,298	13	830	486					
Menard	2,336			96	522	3,071	1							
Midland	2,339			2,537	966	4,631	2							
Milam	2,647			2,929	499	72,382	27	609	168				878	484
Mills	1,941			867	596	24,160	12	817	294				87	132

Mitchell	2,372					12,263	5	55	45					74	306
Montague	2,426			1,084	596	60,472	25	918	388					345	377
Montgomery	2,795	1	6	136	478	22,533	8	106	148						
Moore	2,358			9,826	1,006										
Morris	672	6	29	67	558										
Motley	2,563			349	927										
Nacogdoches	2,550			256	558	51,184	20	234	117						
Navarro	2,815			3,115	499	52,175	19	1,263	190						
Newton	2,452			119	478	8,619	4	132	97						
Nueces	2,175													18	70
Ochiltree	2,377			9,906	1,006	16,726	7	49	39					3,502	670
Oldham	3,896			16,237	1,006	922	0							1,891	874
Orange	988					5,894	6								
Palo Pinto	2,551			1,139	596	35,535	14	255	107					81	199
Panola	2,137			214	558	41,869	20	145	125						
Parker	2,356			1,052	596	80,518	34	270	78			1	4		
Parmer	2,298			9,575	1,006	22,596	10	2,443	448					7,650	715
Pecos	12,370			975	348	21,086	2								
Polk	2,883	1	5	140	478	20,242	7	111	125						
Potter	2,390			9,961	1,006	2,680	1	27	74						
Presidio	10,045			792	348	2,893	0								
Rains	672			67	558										
Randall	2,391			9,966	1,006	25,616	11	522	139					6,374	847
Reagan	3,047			125	522	5,037	2								
Real	1,812			74	522	1,428	1								
Red River	2,752			276	558	61,304	22	1,050	167						
Reeves	6,870			541	348	11,506	2	266	135					4,747	805
Refugio	2,119														
Roberts	2,394			9,975	1,006										
Robertson	2,244			109	478	85,744	38	842	116						
Rockwall	385			426	499	9,376	24								
Runnels	2,736					21,070	8	1,007	269					1,074	317
Rusk	2,438	1	4	244	558	56,210	23	144	124						
Sabine	1,490			72	478										
San Augustine	1,541			75	478										
San Jacinto	1,630			79	478	12,772	8	278	362						
San Saba	2,946			121	522	20,464	7	21	48						
Schleicher	3,393			139	522	2,442	1	236	173						
Scurry	2,351					16,023	7	338	111					3,924	382
Shackelford	2,370			1,058	596	8,222	3	84	82						
Shelby	2,166			217	558	36,498	17	64	92						
Sherman	2,393			9,972	1,006										
Smith	2,464			247	558	86,829	35	876	227						
Somervell	497			222	596	8,949	18	27	79						
Starr	3,181			946	623	23,924	8	138	68						
Stephens	2,384			1,065	596										
Sterling	2,392			98	522	372	0								
Sutton	3,766			155	522										
Swisher	2,335			9,729	1,006	10,746	5	129	145					1,775	464
Tarrant	2,324			2,571	499	27,120	12	203	266						
Taylor	2,379					20,075	8	361	105			1	6	918	224
Terrell	6,117			482	348	455	0								
Terry	2,311			2,507	966										
Throckmorton	2,369			1,058	596										
Titus	1,105			111	558	33,209	30	317	120						
Tom Green	3,989			164	522	12,017	3	1,187	332					3,785	407
Travis	2,646			475	625	25,933	10	115	79						
Trinity	1,854	2	7	90	478	23,755	13	97	148						
Tyler	2,432	4	10	118	478	15,489	6	18	44						
Upshur	1,540			154	558	51,125	33	415	311						
Upton	3,221			132	522	515	0								
Uvalde	4,035			166	522										
Val Verde	8,390			345	522	4,543	1								
Van Zandt	2,228			223	558	122,580	55	1,717	252						
Victoria	2,301					23,334	10	306	156						
Walker	2,080			101	478	28,253	14	49	66						
Waller	1,345	1	4	65	478	46,068	34	1,260	206					37	162
Ward	2,173			171	348	183	0								
Washington	1,611			289	625	74,396	46	103	39					13	96
Webb	8,740			221	332	6,399	1								
Wharton	2,837					54,498	19	147	46					1,902	606
Wheeler	2,370			323	927	25,830	11	950	174						
Wichita	1,638			223	927	27,599	17	100	124					338	314
Wilbarger	2,532			345	927	58,379	23	82	68					314	170
Willacy	1,548			460	623										
Williamson	2,937			3,250	499	48,977	17	339	104					246	196
Wilson	2,093			375	625	64,390	31	725	230					2,228	521
Winkler	2,185			172	348										
Wise	2,389			1,067	596	115,645	48	969	196					573	364
Wood	1,806			181	558	88,378	49	2,901	228					213	377
Yoakum	2,077			2,252	966	10,705	5	1,240	167						
Young	2,409			1,076	596	24,520	10	233	91					52	130

Vegetables

County	Area (Km^2)	Cabbage		Cantaloupe		Carrot		Chili Pepper		Cucumber		Onion	
		P	NPP	P	NPP	P	NPP	P	NPP	P	NPP	P	NPP
Anderson	2,797			0.09	1								
Andrews	3,896												
Angelina	2,247			0.01	1							5	219
Atascosa	3,198			0.07	1			3	76				
Austin	1,701												
Bailey	2,148												
Bandera	2,064			0.00	1			0.31	76			0.89	219
Bastrop	2,320							0.92	76	0.23	56		
Bell	2,817							0.31	76	0.23	56	0.89	219
Bexar	3,253			0.01	1							0.89	219
Blanco	1,847												
Bowie	2,404			0.01	1			0.31	76	0.23	56	2	219
Brazoria	3,856	101	188	0.27	1			0.92	76			186	219
Brazos	1,529			0.00	1							0.89	219
Brewster	16,094							0.61	76			3	219
Burleson	1,756												
Burnet	2,643												
Caldwell	1,417												
Calhoun	1,065												
Callahan	2,332			0.03	1			0.61	76	0.68	56		
Cameron	2,481	241	188							20	56	333	219
Cass	2,498			0.01	1								
Cherokee	2,758			0.05	1			4	76			5	219
Clay	2,886												
Collin	2,295			0.14	1			0.61	76			4	219
Comanche	2,453			0.89	1								
Cooke	2,323											3	219
Coryell	2,736			0.03	1								
Dallas	2,354			0.02	1			0.31	76			0.89	219
Deaf Smith	3,887					19	33					43	219
Denton	2,481			0.03	1			0.31	76			10	219
Dimmit	3,454												
Donley	2,416			0.23	1								
Eastland	2,412			0.06	1								
El Paso	2,656											553	219
Ellis	2,465			0.01	1							4	219
Erath	2,820			0.09	1							2	219
Falls	2,005							0.61	76	0.23	56		
Fannin	2,332												
Fayette	2,486			0.01	1					0.68	56		
Fisher	2,335												
Floyd	2,572												
Fort Bend	2,299					0.13	33			0.45	56		
Freestone	2,313			0.06	1			2	76			14	219
Frio	2,935	581	188			0.27	33					319	219
Gaines	3,900												
Galveston	1,065												
Gillespie	2,747			0.03	1			2	76	2	56	15	219
Glasscock	2,335			0.01	1								
Goliad	2,225												
Gonzales	2,770			0.02	1			2	76			3	219
Grayson	2,536												
Gregg	718												
Grimes	2,078												
Guadalupe	1,849			0.01	1			0.61	76			3	219
Hale	2,605												
Hall	2,341									554	56		
Hardeman	1,803												
Hardin	2,334							0.31	76				
Harris	4,607							2	76	12	56	0.89	219
Harrison	2,379			0.00	1								
Hays	1,759			0.01	1							0.89	219
Henderson	2,461			0.06	1			0.61	76			5	219
Hidalgo	4,099	2,402	188	9	1	313	33	137	76	635	56	7,767	219
Hill	2,553			0.32	1			0.31	76	0.23	56	0.89	219
Hockley	2,357									74	56		
Hood	1,131			0.03	1								
Hopkins	2,056			0.01	1			0.61	76			0.89	219
Hudspeth	11,938							1,175	76				
Hunt	2,287			0.99	1			0.61	76			4	219
Jackson	2,221			0.01	1								
Jasper	2,524			0.01	1			0.61	76			0.89	219
Jefferson	2,576			0.00	1					0.23	56		
Jim Wells	2,248												
Johnson	1,902			0.01	1								
Jones	2,426			0.08	1					0.45	56		
Kaufman	2,091							0.31	76			11	219
Kerr	2,867												
Knox	2,214											2	219
La Salle	3,867			0.17	1								
Lamar	2,417												
Lamb	2,640												
Lampasas	1,848											3	219
Lavaca	2,513												

Lee	1,643			0.01	1			4	76				
Leon	2,802			0.01	1								
Liberty	3,056			0.03	1			0.92	76				
Limestone	2,418			0.05	1			0.92	76	0.45	56	6	219
Live Oak	2,792												
Lubbock	2,335			0.01	1			0.92	76	0.23	56	0.89	219
Lynn	2,316			0.01	1								
Mason	2,412												
Maverick	3,346			0.16	1								
McLennan	2,746							0.31	76	0.23	56	0.89	219
Medina	3,453	270	188	0.23	1			10	76	420	56	43	219
Midland	2,339												
Milam	2,647			0.01	1			0.31	76	0.45	56	2	219
Mitchell	2,372			0.12	1								
Montague	2,426			0.55	1			0.92	76			5	219
Montgomery	2,795							0.92	76				
Morris	672												
Nacogdoches	2,550			0.00	1			2	76	1	56	4	219
Navarro	2,815			0.01	1			0.31	76	0.23	56	0.89	219
Palo Pinto	2,551			0.06	1							0.89	219
Panola	2,137							2	76				
Parker	2,356			0.10	1			0.61	76			5	219
Parmer	2,298												
Pecos	12,370			3	1								
Polk	2,883			0.02	1					0.90	56		
Rains	672			0.00	1							0.89	219
Red River	2,752												
Robertson	2,244			0.01	1			0.31	76			2	219
Runnels	2,736												
Rusk	2,438			0.00	1			0.31	76			2	219
Sabine	1,490												
San Augustine	1,541			0.03	1			0.31	76				
San Jacinto	1,630												
San Patricio	1,830												
San Saba	2,946							0.61	76				
Shelby	2,166												
Smith	2,464			0.06	1			5	76	3	56	63	219
Somervell	497			0.01	1								
Starr	3,181			2	1							357	219
Tarrant	2,324											2	219
Taylor	2,379												
Terry	2,311			0.04	1								
Travis	2,646			0.01	1			0.92	76			2	219
Tyler	2,432							0.31	76				
Upshur	1,540			0.04	1			0.31	76			10	219
Uvalde	4,035	892	188					0.61	76	686	56	758	219
Van Zandt	2,228			0.01	1			6	76	5	56	5	219
Victoria	2,301									3	56		
Waller	1,345			0.02	1			0.92	76	0.68	56	3	219
Washington	1,611			0.01	1			0.31	76			0.89	219
Webb	8,740												
Wharton	2,837			0.01	1					0.68	56		
Wheeler	2,370			0.02	1								
Williamson	2,937			0.01	1			0.92	76	0.23	56	3	219
Wilson	2,093			0.01	1								
Wise	2,389			0.62	1					0.68	56	3	219
Wood	1,806			0.01	1			0.31	76			6	219
Yoakum	2,077												
Zapata	2,738												
Zavala	3,369	378	188	0.61	1	0.13	33					687	219

Vegetables (continued)

County	Area (Km^2)	Pumpkin		Spinach		Snap Beans		Sweet Corn		Tomato		Watermelon	
		P	NPP	P	NPP	P	NPP	P	NPP	P	NPP	P	NPP
Anderson	2,797					7	83	119	1,011	11	81	64	101
Andrews	3,896												
Angelina	2,247					0.34	83			4	81	21	101
Atascosa	3,198									5	81	154	101
Austin	1,701							12	1,011	0.33	81		
Bailey	2,148	106	119									37	101
Bandera	2,064									0.99	81	0.82	101
Bastrop	2,320									2	81	47	101
Bell	2,817									0.33	81		
Bexar	3,253							225	1,011	0.99	81	53	101
Blanco	1,847									0.99	81		
Bowie	2,404	7	119			0.67	83	94	1,011	0.99	81	10	101
Brazoria	3,856					218	83	45	1,011	19	81	103	101
Brazos	1,529									4	81	2	101
Brewster	16,094									0.33	81		
Burleson	1,756											166	101
Burnet	2,643					1	83			0.33	81		
Caldwell	1,417											16	101
Calhoun	1,065											0.82	101
Callahan	2,332									2	81	2	101
Cameron	2,481							205	1,011			155	101
Cass	2,498							12	1,011	2	81	50	101
Cherokee	2,758					58	83	45	1,011	7	81	63	101
Clay	2,886											2	101
Collin	2,295							4	1,011	2	81	13	101
Comanche	2,453									2	81	564	101
Cooke	2,323							16	1,011	0.66	81	2	101
Coryell	2,736												
Dallas	2,354									0.66	81	3	101
Deaf Smith	3,887												
Denton	2,481									2	81	6	101
Dimmit	3,454									0.66	81	14	101
Donley	2,416									2	81	183	101
Eastland	2,412											106	101
El Paso	2,656									0.33	81		
Ellis	2,465							74	1,011	0.99	81	2	101
Erath	2,820									4	81	43	101
Falls	2,005					4	83			0.99	81	18	101
Fannin	2,332	5	119										
Fayette	2,486									2	81		
Fisher	2,335											9	101
Floyd	2,572	369	119									66	101
Fort Bend	2,299							16	1,011				
Freestone	2,313									2	81	20	101
Frio	2,935			248	71							407	101
Gaines	3,900											716	101
Galveston	1,065											9	101
Gillespie	2,747									28	81	6	101
Glasscock	2,335											7	101
Goliad	2,225											2	101
Gonzales	2,770									3	81	40	101
Grayson	2,536							123	1,011				
Gregg	718									0.33	81	6	101
Grimes	2,078									6	81	38	101
Guadalupe	1,849							29	1,011	0.66	81	3	101
Hale	2,605							6,252	1,011				
Hall	2,341												
Hardeman	1,803											156	101
Hardin	2,334					0.34	83	4	1,011	0.99	81	2	101
Harris	4,607					8	83	188	1,011	8	81	11	101
Harrison	2,379									2	81	16	101
Hays	1,759					1	83	4	1,011	1	81		
Henderson	2,461							45	1,011	2	81	62	101
Hidalgo	4,099			201	71			1,064	1,011	122	81	4,119	101
Hill	2,553									0.66	81	104	101
Hockley	2,357												
Hood	1,131												
Hopkins	2,056									0.99	81	7	101
Hudspeth	11,938												
Hunt	2,287	42	119							1	81	17	101
Jackson	2,221											2	101
Jasper	2,524					2	83	82	1,011	3	81	15	101
Jefferson	2,576									0.33	81		
Jim Wells	2,248											839	101
Johnson	1,902									1	81	2	101
Jones	2,426									2	81	16	101
Kaufman	2,091							4	1,011	3	81	0.82	101
Kerr	2,867									0.33	81		
Knox	2,214												
La Salle	3,867											125	101

Lamar	2,417									0.66	81	24	101
Lamb	2,640	146	119										
Lampasas	1,848									7	81		
Lavaca	2,513									0.33	81		
Lee	1,643									2	81	28	101
Leon	2,802									0.33	81	50	101
Liberty	3,056									3	81	9	101
Limestone	2,418					0.67	83	45	1,011	4	81	63	101
Live Oak	2,792							8	1,011	0.66	81	19	101
Lubbock	2,335							49	1,011	6	81	57	101
Lynn	2,316									0.33	81	3	101
Mason	2,412											25	101
Maverick	3,346									3	81		
McLennan	2,746									0.66	81		
Medina	3,453					46	83	155	1,011	8	81	42	101
Midland	2,339									0.33	81		
Milam	2,647									3	81	30	101
Mitchell	2,372											11	101
Montague	2,426					0.34	83			6	81	43	101
Montgomery	2,795					3	83	25	1,011	3	81	0.41	101
Morris	672							12	1,011	2	81	2	101
Nacogdoches	2,550									3	81		
Navarro	2,815							8	1,011	0.99	81	2	101
Palo Pinto	2,551									0.99	81		
Panola	2,137							4	1,011	2	81	10	101
Parker	2,356									3	81	27	101
Parmer	2,298	355	119			0.00	83					206	101
Pecos	12,370												
Polk	2,883					2	83	70	1,011	4	81	8	101
Rains	672									0.99	81		
Red River	2,752							8	1,011	0.33	81	24	101
Robertson	2,244							8	1,011	1	81	8	101
Runnels	2,736											9	101
Rusk	2,438									6	81	91	101
Sabine	1,490							37	1,011				
San Augustine	1,541									2	81		
San Jacinto	1,630					0.67	83			0.66	81		
San Patricio	1,830									13	81		
San Saba	2,946									0.66	81		
Shelby	2,166											326	101
Smith	2,464	22	119			5	83	94	1,011	14	81	129	101
Somervell	497									0.33	81	1	101
Starr	3,181												
Tarrant	2,324												
Taylor	2,379									0.33	81	5	101
Terry	2,311											640	101
Travis	2,646					0.34	83	12	1,011	3	81	0.41	101
Tyler	2,432					0.34	83	20	1,011	2	81	11	101
Upshur	1,540							20	1,011	5	81	24	101
Uvalde	4,035			300	71	58	83			1	81		
Van Zandt	2,228					11	83			30	81	69	101
Victoria	2,301							53	1,011	0.99	81	3	101
Waller	1,345									12	81	239	101
Washington	1,611									1	81	13	101
Webb	8,740									7	81	4	101
Wharton	2,837									2	81	18	101
Wheeler	2,370											11	101
Williamson	2,937							20	1,011	2	81		
Wilson	2,093											251	101
Wise	2,389					0.67	83	4	1,011	3	81	216	101
Wood	1,806					4	83	110	1,011	7	81	86	101
Yoakum	2,077											1,717	101
Zapata	2,738									10	81		
Zavala	3,369			317	71							62	101

Fruits

County	Area (Km^2)	Citrus		Grape		Peach		Pecan	
		P	NPP	P	NPP	P	NPP	P	NPP
Anderson	2,797			50	1,533	144	850	2,140	1,612
Andrews	3,896							959	1,612
Angelina	2,247			12	1,533			20	1,612
Archer	2,396							91	1,612
Atascosa	3,198					28	850	2,511	1,612
Austin	1,701			211	1,533			2,851	1,612
Bandera	2,064					48	850	1,650	1,612
Bastrop	2,320			25	1,533	69	850	15,682	1,612
Bee	2,279							235	1,612
Bell	2,817			31	1,533	65	850	21,377	1,612
Bexar	3,253							2,479	1,612
Blanco	1,847			391	1,533	230	850	639	1,612
Borden	2,348							11,683	1,612
Bosque	2,596			19	1,533			11,683	1,612
Bowie	2,404					48	850	14,919	1,612
Brazoria	3,856							3,477	1,612
Brazos	1,529							2,068	1,612
Brewster	16,094							10,176	1,612
Briscoe	2,335							2,675	1,612
Brown	2,476							10,176	1,612
Burnet	2,643			242	1,533	38	850	2,675	1,612
Caldwell	1,417			25	1,533			7,502	1,612
Callahan	2,332					28	850	1,442	1,612
Cameron	2,481	62,061	4,882					7	1,612
Camp	528			25	1,533	505	850		
Chambers	1,649							59	1,612
Cherokee	2,758					402	850	130	1,612
Clay	2,886					633	850		
Coke	2,403							124	1,612
Coleman	3,317							1,350	1,612
Collin	2,295					34	850	2,896	1,612
Colorado	2,524							12,929	1,612
Comal	1,487					48	850	391	1,612
Comanche	2,453					93	850	93,119	1,612
Cooke	2,323							13,705	1,612
Coryell	2,736			87	1,533			10,659	1,612
Crane	2,039							111	1,612
Dallas	2,354					28	850	1,605	1,612
Dawson	2,339			1,011	1,533				
Delta	721							117	1,612
Denton	2,481			25	1,533	76	850	2,759	1,612
DeWitt	2,358							13,418	1,612
Eastland	2,412			6	1,533	217	850	10,033	1,612
Ector	2,340							1,337	1,612
El Paso	2,656			25	1,533	10	850	54,019	1,612
Ellis	2,465					10	850	1,611	1,612
Erath	2,820					58	850	12,244	1,612
Falls	2,005							3,301	1,612
Fannin	2,332			168	1,533	124	850	5,577	1,612
Fayette	2,486			25	1,533	21	850	5,753	1,612
Fisher	2,335							959	1,612
Fort Bend	2,299			105	1,533	28	850	5,616	1,612
Franklin	765					79	850	450	1,612
Freestone	2,313							411	1,612
Gaines	3,900							1,729	1,612
Galveston	1,065			50	1,533			333	1,612
Gillespie	2,747					3,706	850	2,061	1,612
Glasscock	2,335							1,174	1,612
Goliad	2,225							72	1,612
Gonzales	2,770					3	850	32,048	1,612
Grayson	2,536			273	1,533	24	850	5,884	1,612
Gregg	718					45	850	137	1,612
Grimes	2,078							848	1,612
Guadalupe	1,849					10	850	20,365	1,612
Hale	2,605			1,024	1,533			78	1,612
Hamilton	2,165							13,647	1,612
Hardeman	1,803							78	1,612
Hardin	2,334							222	1,612
Harris	4,607							3,105	1,612
Harrison	2,379					10	850	170	1,612
Hays	1,759			161	1,533	141	850	822	1,612
Henderson	2,461					65	850	1,266	1,612
Hidalgo	4,099	503,782	4,882						
Hill	2,553			56	1,533	76	850	1,598	1,612
Hockley	2,357			205	1,533	3	850	802	1,612
Hood	1,131			62	1,533			18,154	1,612
Hopkins	2,056							261	1,612
Houston	3,209			12	1,533	45	850	9,126	1,612
Howard	2,343							483	1,612
Hunt	2,287			37	1,533	38	850	5,506	1,612

Irion	2,724							241	1,612
Jack	2,382							2,087	1,612
Jackson	2,221							2,251	1,612
Jasper	2,524							150	1,612
Jeff Davis	5,894			298	1,533			183	1,612
Jefferson	2,576							926	1,612
Jim Hogg	2,941							98	1,612
Jim Wells	2,248							104	1,612
Johnson	1,902					10	850	1,487	1,612
Jones	2,426							594	1,612
Karnes	1,951							607	1,612
Kaufman	2,091					162	850	626	1,612
Kendall	1,716			56	1,533	58	850	665	1,612
Kerr	2,867							1,383	1,612
Kimble	3,238							5,858	1,612
La Salle	3,867							209	1,612
Lamar	2,417							5,616	1,612
Lampasas	1,848					14	850	6,060	1,612
Lavaca	2,513					21	850	12,962	1,612
Lee	1,643							4,031	1,612
Leon	2,802			6	1,533	28	850	365	1,612
Liberty	3,056					14	850	718	1,612
Limestone	2,418					354	850	1,566	1,612
Llano	2,501			124	1,533			978	1,612
Lubbock	2,335			1,911	1,533			1,846	1,612
Madison	1,225					21	850		
Mason	2,412							2,068	1,612
Matagorda	3,144			37	1,533			7,365	1,612
Maverick	3,346							13,901	1,612
McLennan	2,746					24	850	3,686	1,612
Medina	3,453							4,795	1,612
Menard	2,336							5,799	1,612
Midland	2,339			62	1,533			1,931	1,612
Milam	2,647					28	850	13,875	1,612
Mills	1,941							15,747	1,612
Montague	2,426			192	1,533	444	850	12,433	1,612
Montgomery	2,795					93	850	215	1,612
Morris	672					7	850		
Nacogdoches	2,550					86	850		
Navarro	2,815					103	850	15,101	1,612
Newton	2,452			6	1,533	3	850		
Orange	988	79	4,882						
Palo Pinto	2,551					86	850	17,156	1,612
Panola	2,137			31	1,533	144	850	444	1,612
Parker	2,356			192	1,533	787	850	11,481	1,612
Polk	2,883							65	1,612
Real	1,812					58	850	1,722	1,612
Red River	2,752							3,653	1,612
Robertson	2,244			105	1,533	93	850	3,203	1,612
Rockwall	385							98	1,612
Runnels	2,736							2,290	1,612
Rusk	2,438					275	850	46	1,612
San Augustine	1,541							98	1,612
San Jacinto	1,630					34	850	183	1,612
San Saba	2,946			186	1,533	7	850	52,544	1,612
Scurry	2,351							274	1,612
Smith	2,464			180	1,533	574	850	4,397	1,612
Somervell	497							3,627	1,612
Stephens	2,384							1,155	1,612
Sutton	3,766							1,500	1,612
Swisher	2,335							78	1,612
Tarrant	2,324			68	1,533	31	850	1,246	1,612
Taylor	2,379							757	1,612
Terry	2,311			658	1,533				
Titus	1,105							130	1,612
Tom Green	3,989							2,100	1,612
Travis	2,646			161	1,533	69	850	9,191	1,612
Trinity	1,854							352	1,612
Tyler	2,432					17	850		
Upshur	1,540					230	850	307	1,612
Uvalde	4,035							1,663	1,612
Val Verde	8,390							431	1,612
Van Zandt	2,228			25	1,533	103	850	1,344	1,612
Victoria	2,301							1,409	1,612
Walker	2,080							287	1,612
Waller	1,345					45	850	12,968	1,612
Washington	1,611			50	1,533	28	850	3,451	1,612
Webb	8,740							815	1,612
Wharton	2,837							12,361	1,612
Wichita	1,638							913	1,612
Wilbarger	2,532							26	1,612
Willacy	1,548	3,636	4,882						
Williamson	2,937			37	1,533	144	850	6,380	1,612
Wilson	2,093							2,427	1,612

Wise	2,389			43	1,533	127	850	15,147	1,612
Wood	1,806					217	850	339	1,612
Young	2,409							1,977	1,612
Zavala	3,369							8,650	1,612

APPENDIX C

FIGURES FOR OTHER CROPS

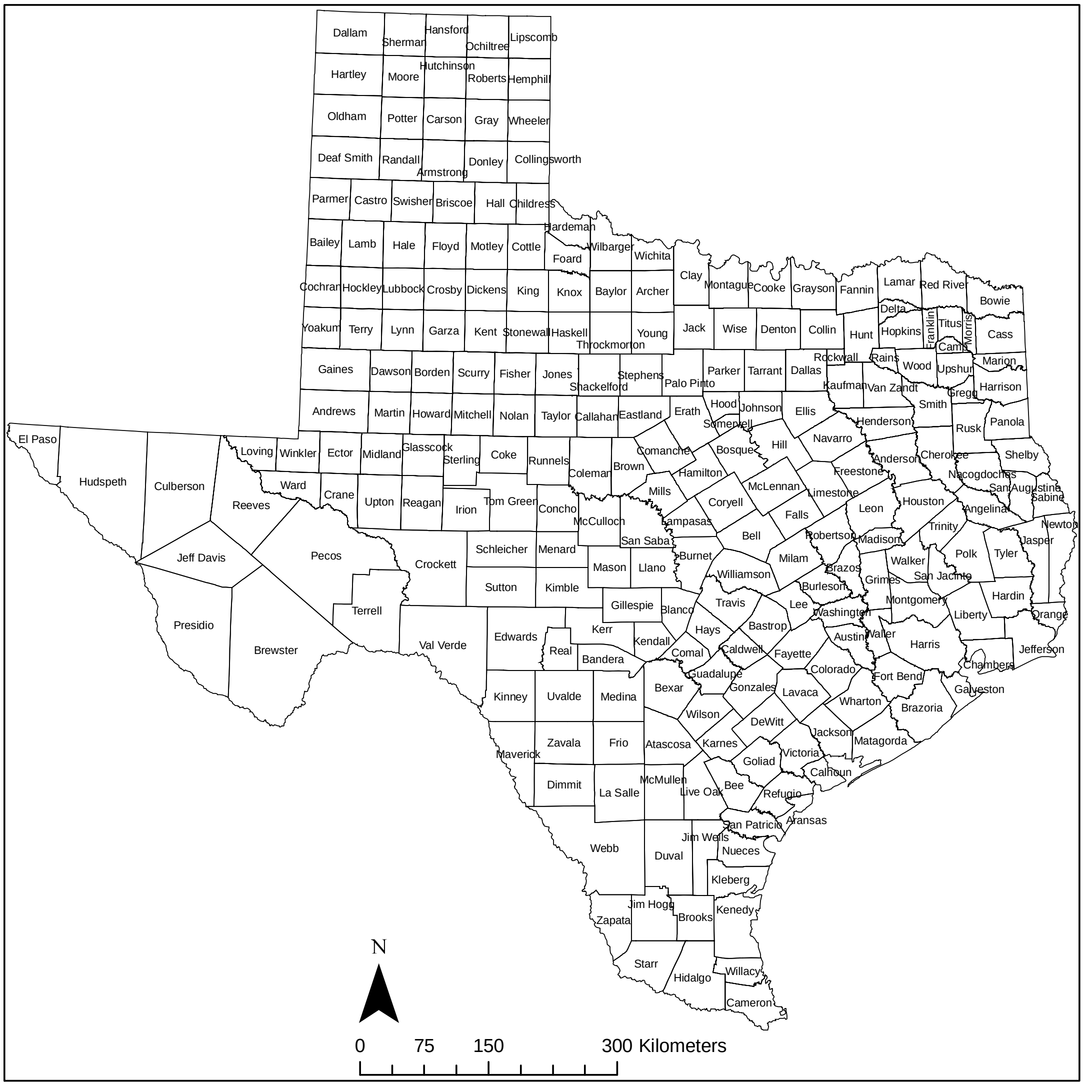

Figure C-1: Texas counties.

Timber

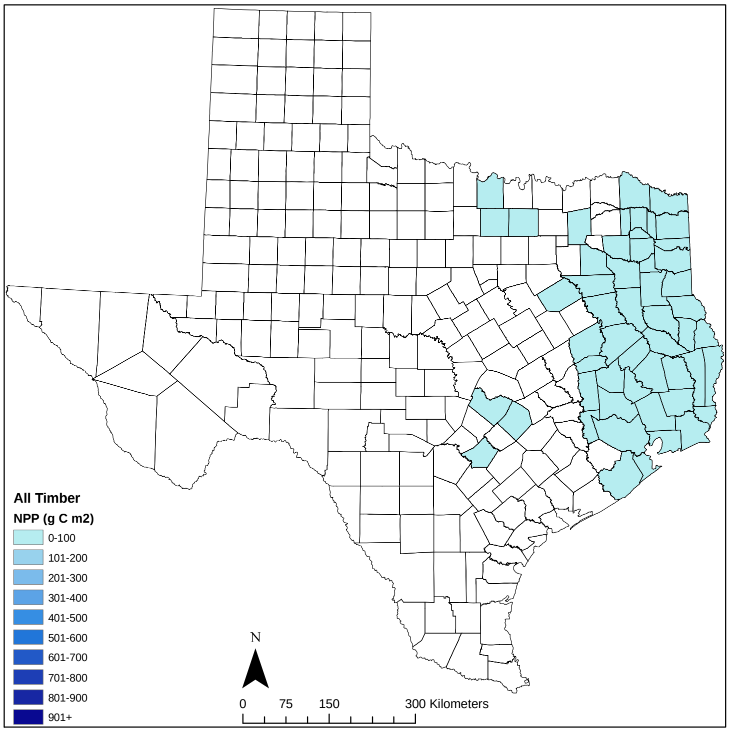

Figure C-2: Average NPP from all timber crops between 2000 and 2005.

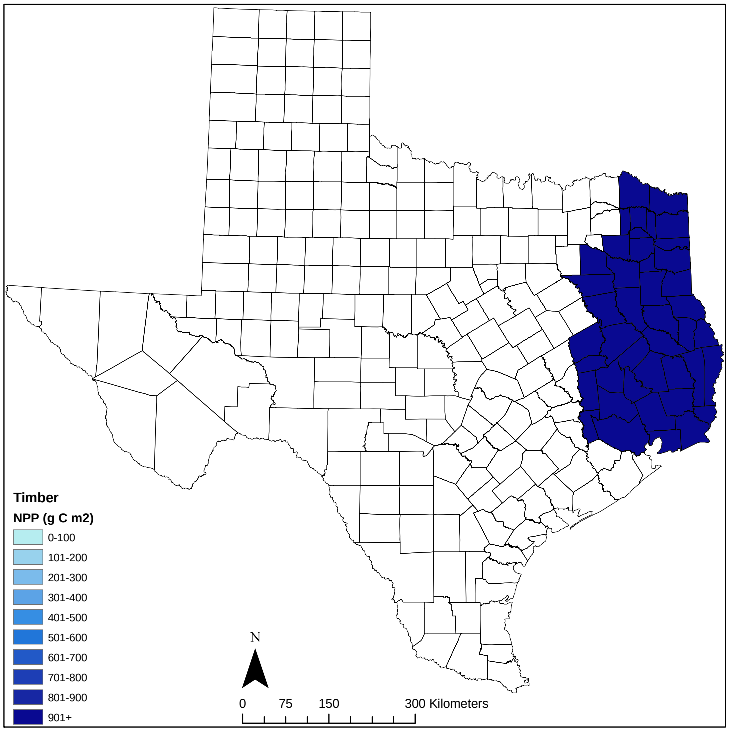

Figure C-3: Average NPP from pine and hardwood lumber between 2000 and 2005.

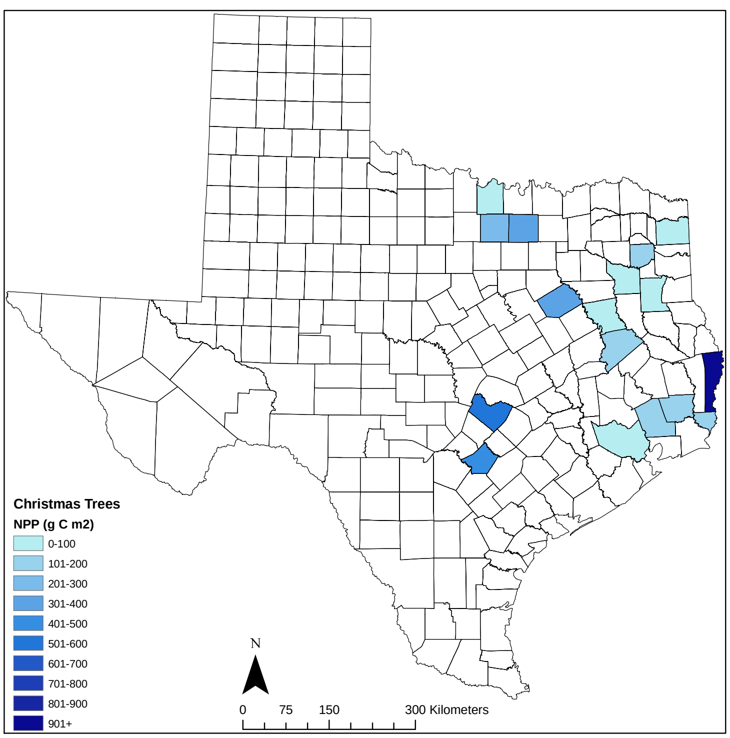

Figure C-4: Average NPP from Christmas trees between 2000 and 2005.

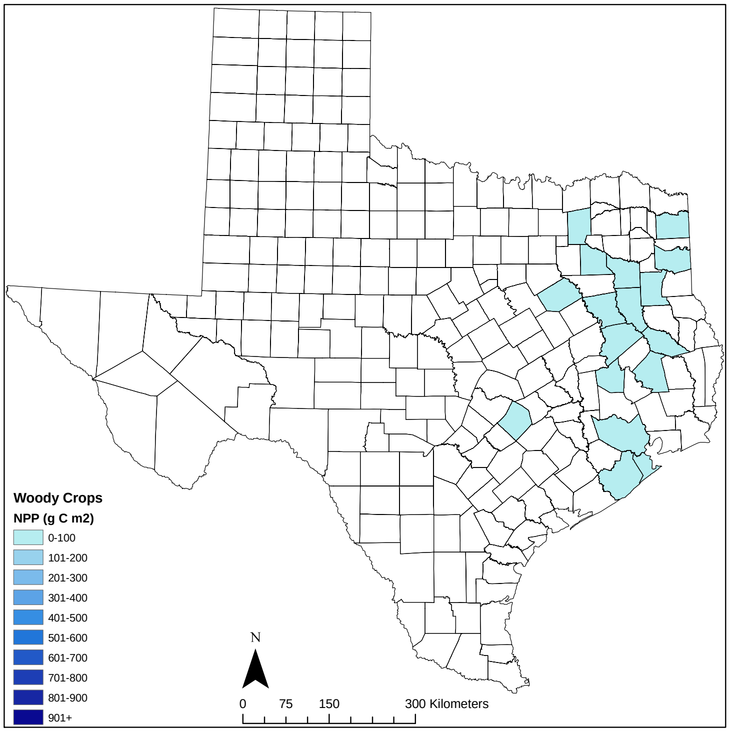

Figure C-5: Average NPP from short-rotation woody crops between 2000 and 2005.

Grains

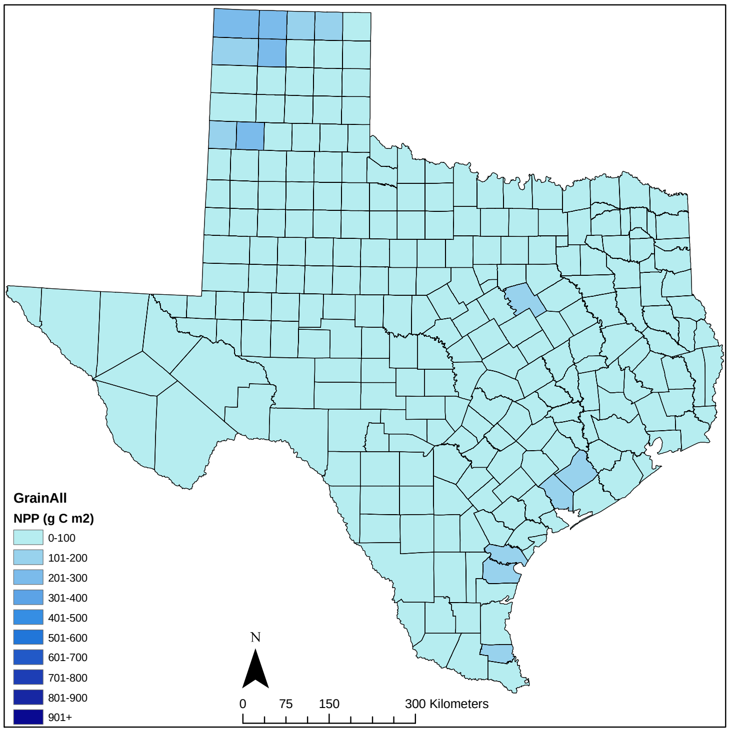

Figure C-6: Average NPP from all grain between 2000 and 2005.

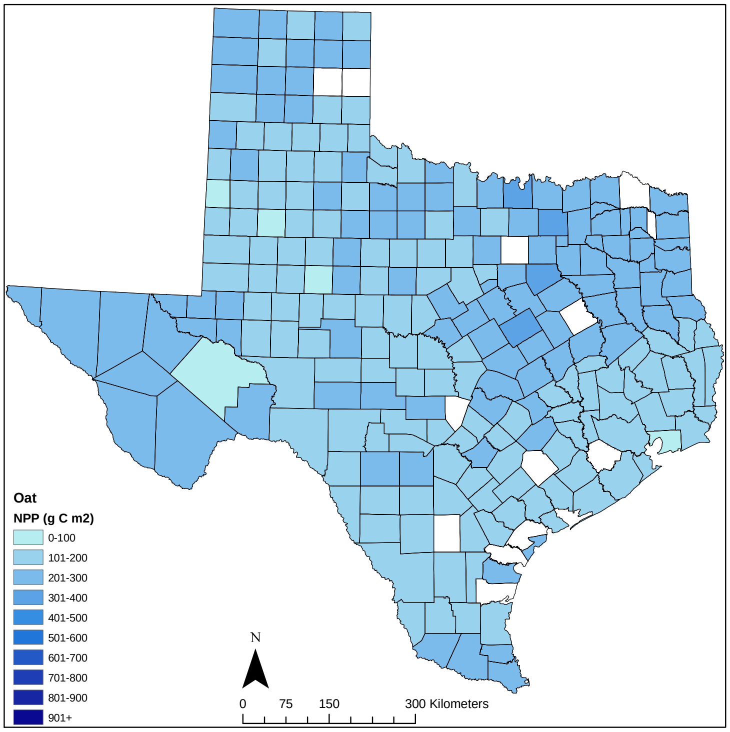

Figure C-7: Average NPP from oat between 2000 and 2005.

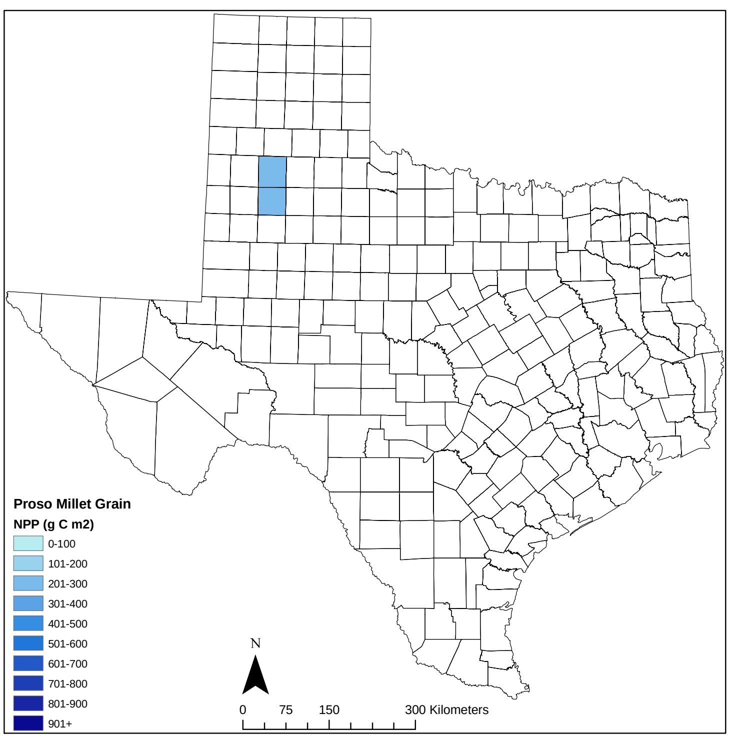

Figure C-8: Average NPP from proso millet grain between 2000 and 2005.

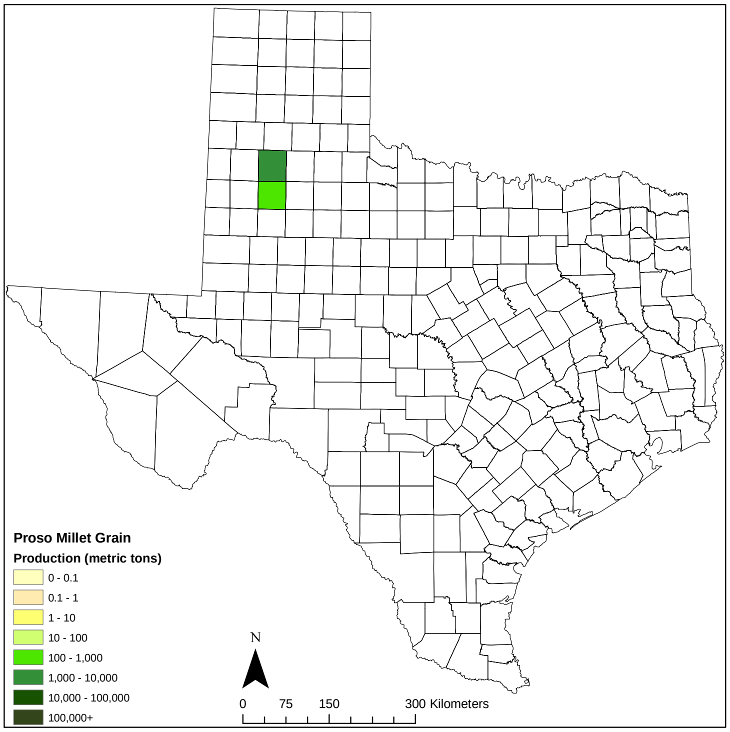

Figure C-9: Average harvested carbon from proso millet grain between 2000 and 2005.

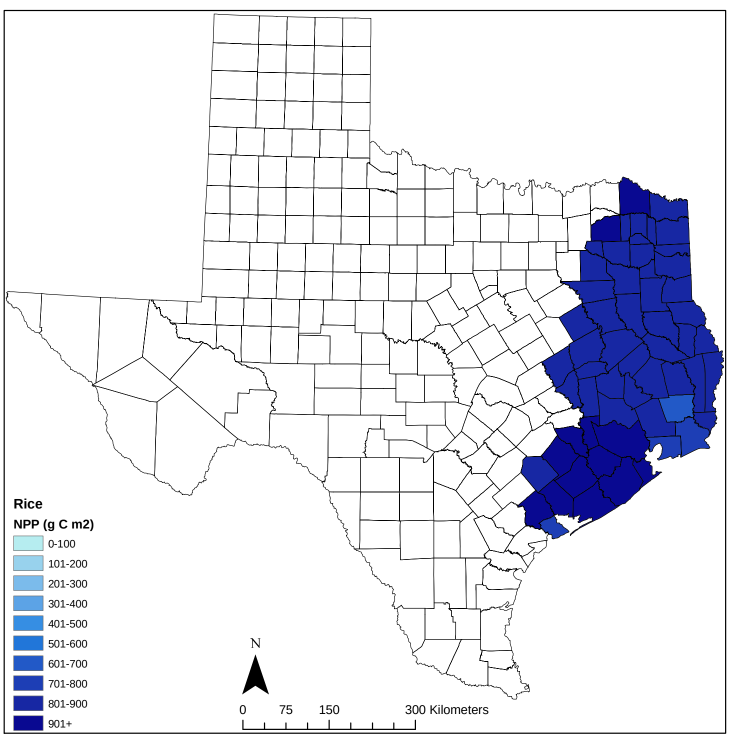

Figure C-10: Average NPP from rice between 2000 and 2005.

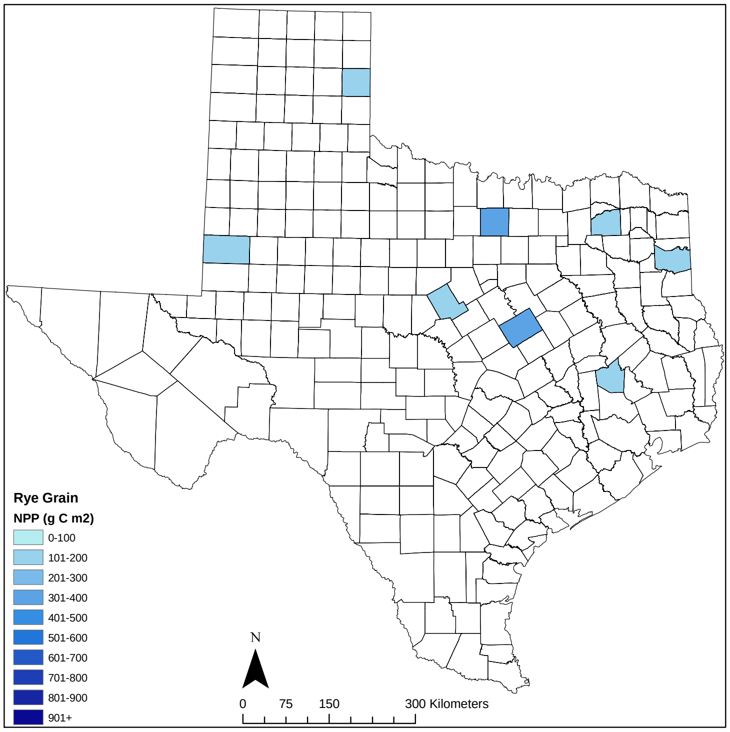

Figure C-11: Average NPP from rye grain between 2000 and 2005.

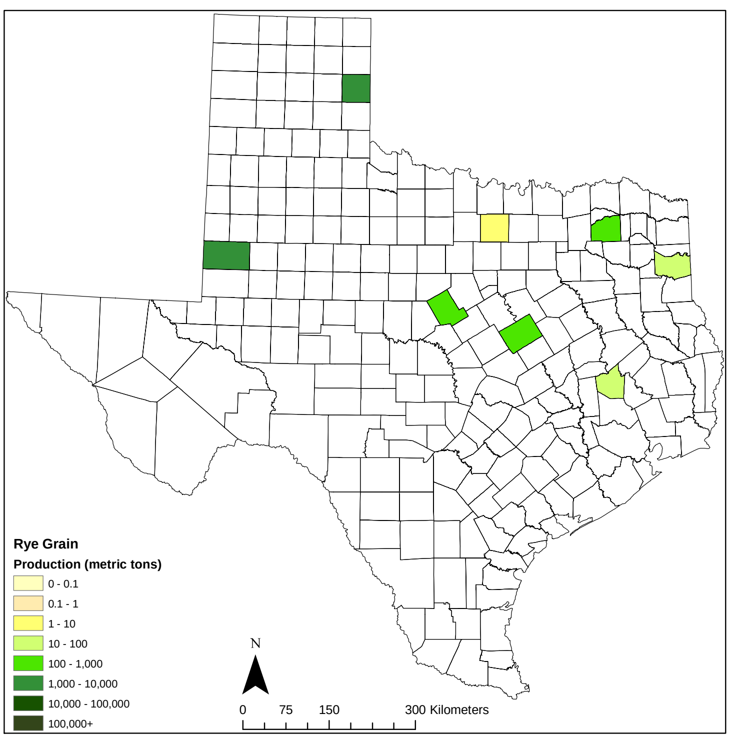

Figure C-12: Average harvested carbon from rye grain between 2000 and 2005.

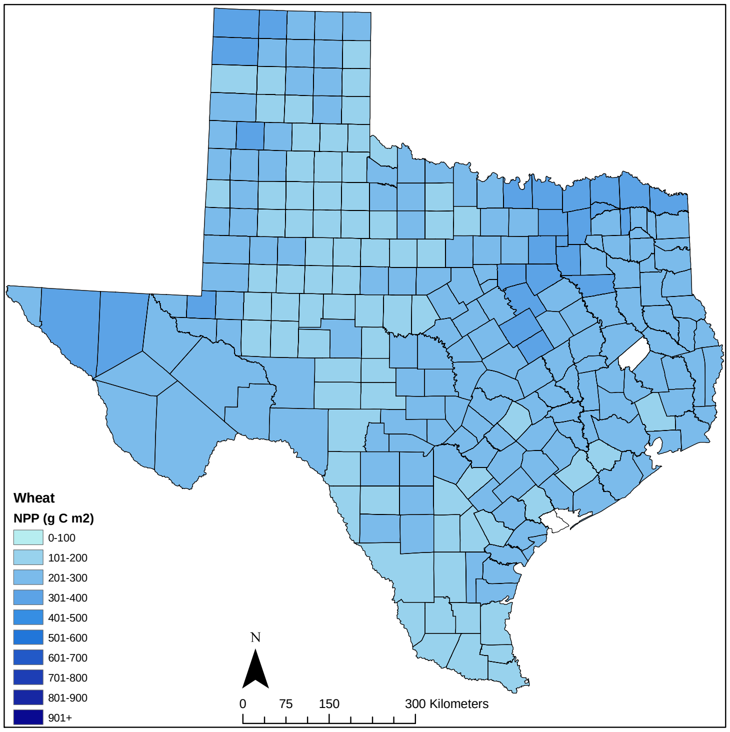

Figure C-13: Average NPP from wheat between 2000 and 2005.

Other Field Crops

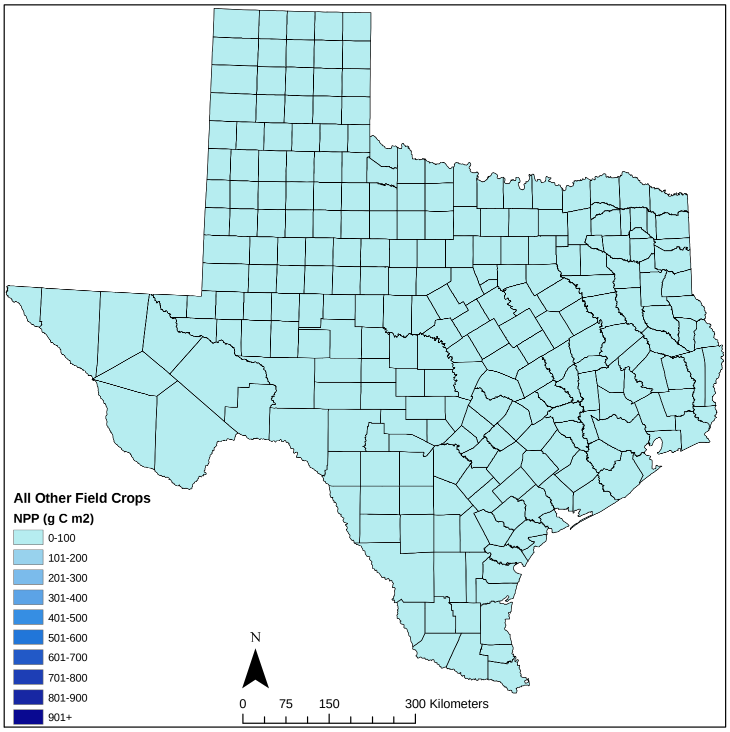

Figure C-14: Average NPP from all 'other field crops' between 2000 and 2005.

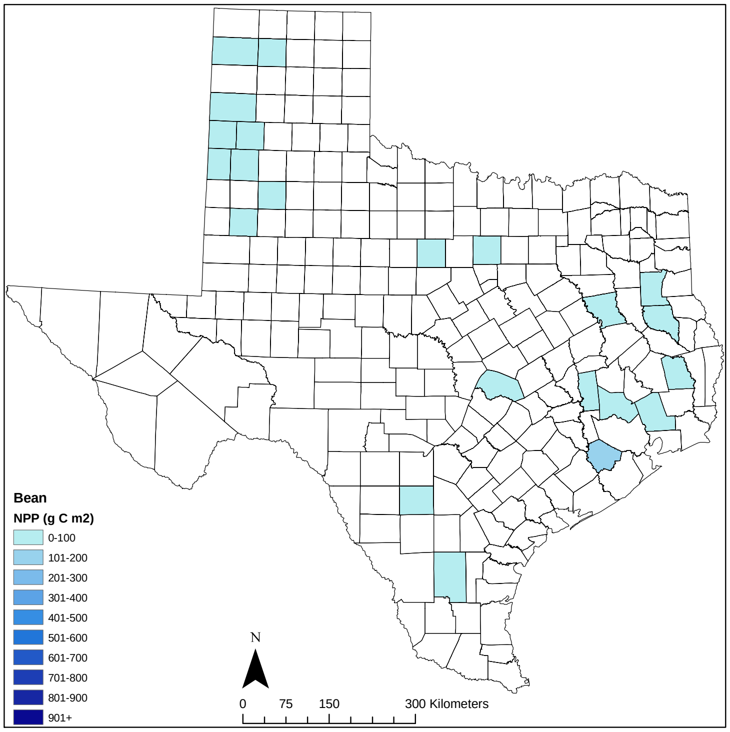

Figure C-15: Average NPP from dry bean between 2000 and 2005.

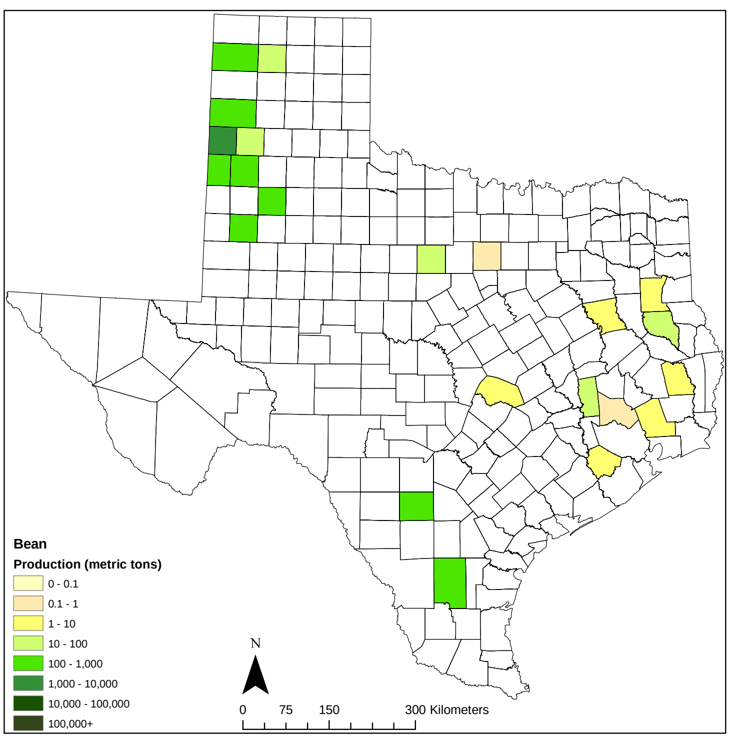

Figure C-16: Average harvested carbon from bean between 2000 and 2005.

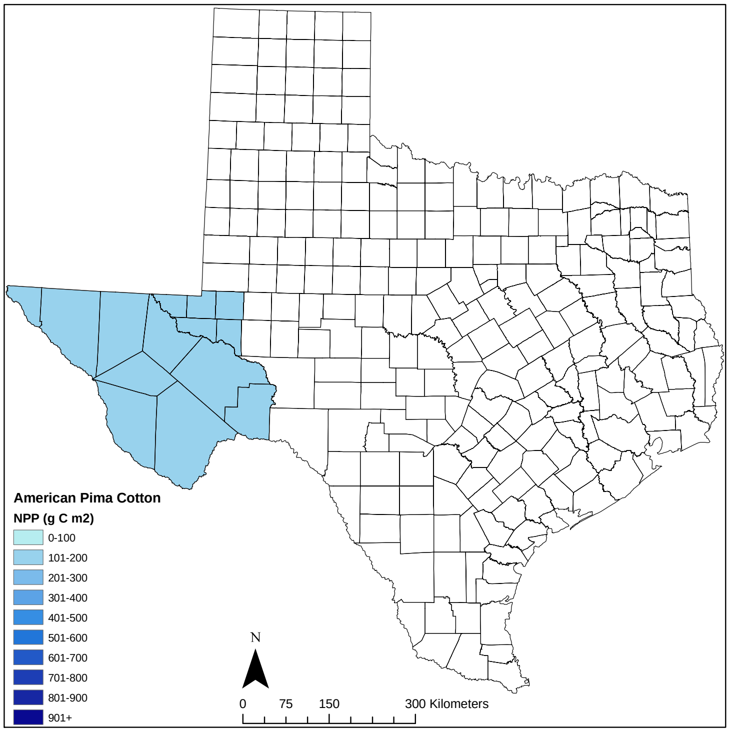

Figure C-17: Average NPP from American Pima cotton between 2000 and 2005.

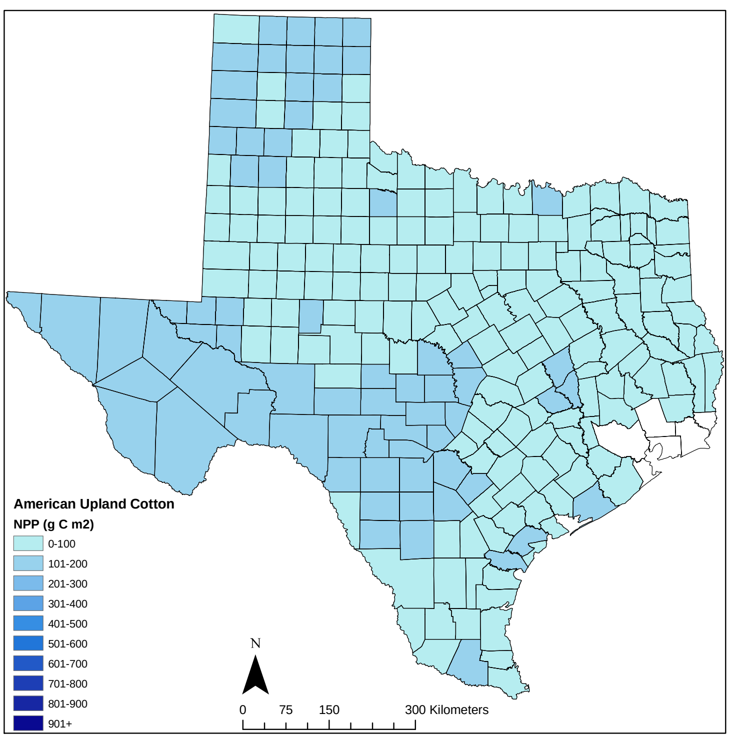

Figure C-18: Average NPP from American Upland cotton between 2000 and 2005.

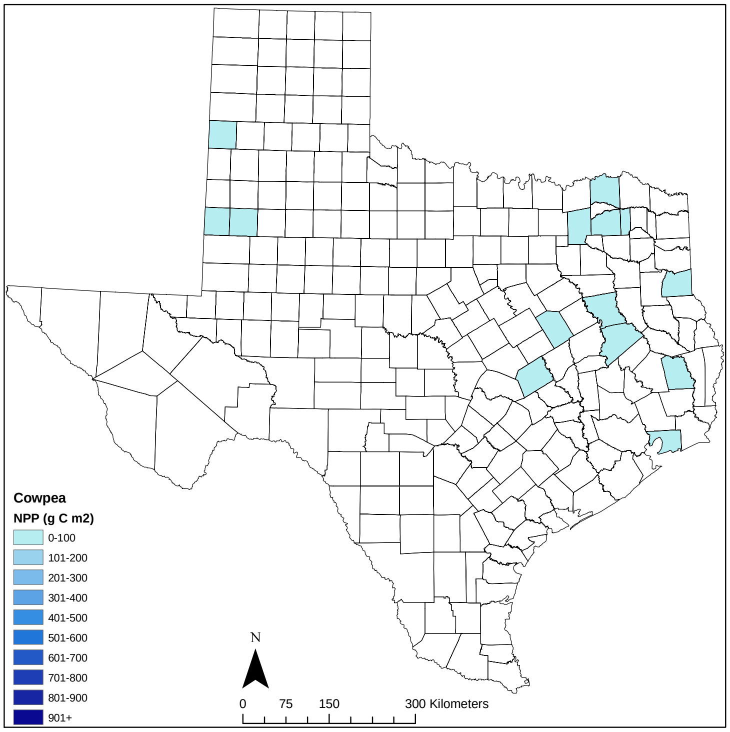

Figure C-19: Average NPP from cowpea between 2000 and 2005.

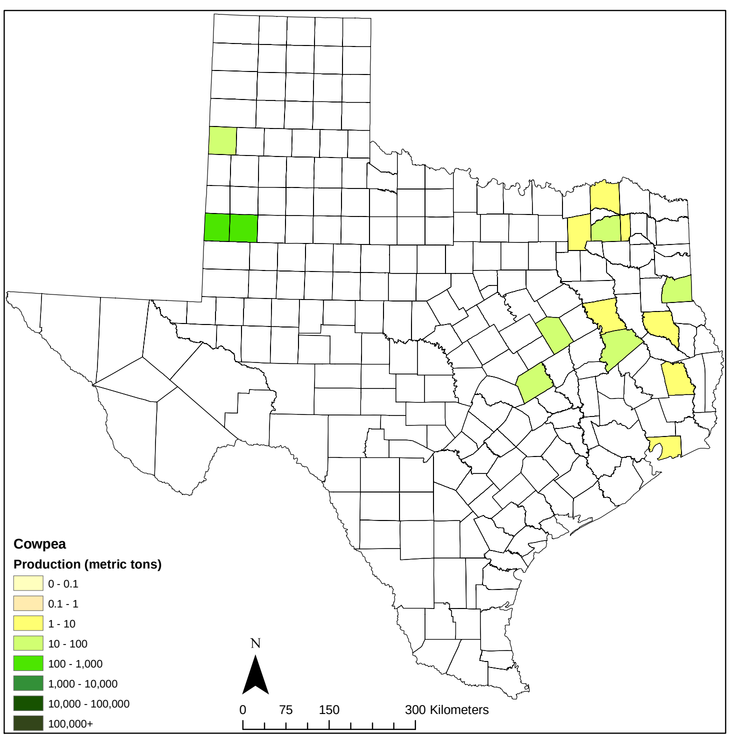

Figure C-20: Average harvested carbon from cowpea between 2000 and 2005.

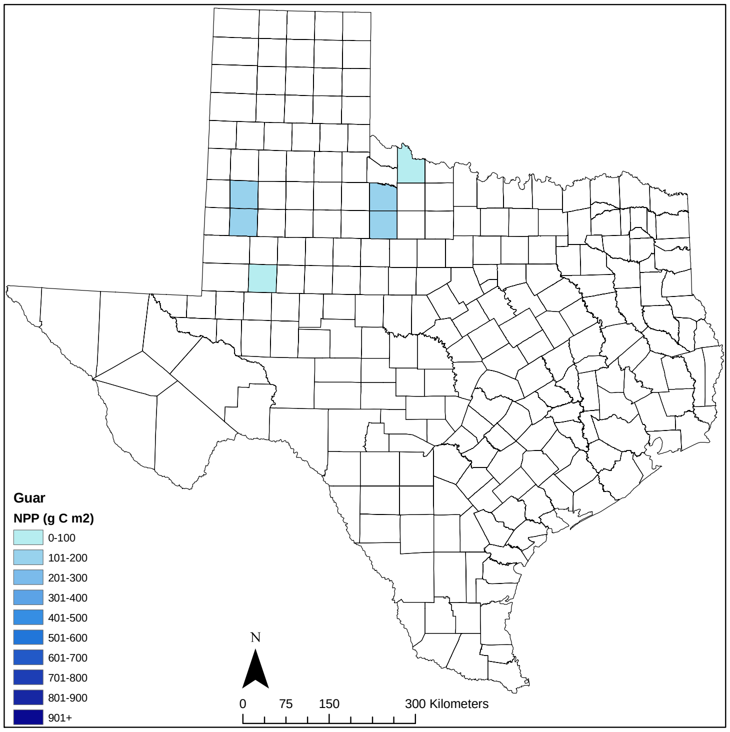

Figure C-21: Average NPP from guar between 2000 and 2005.

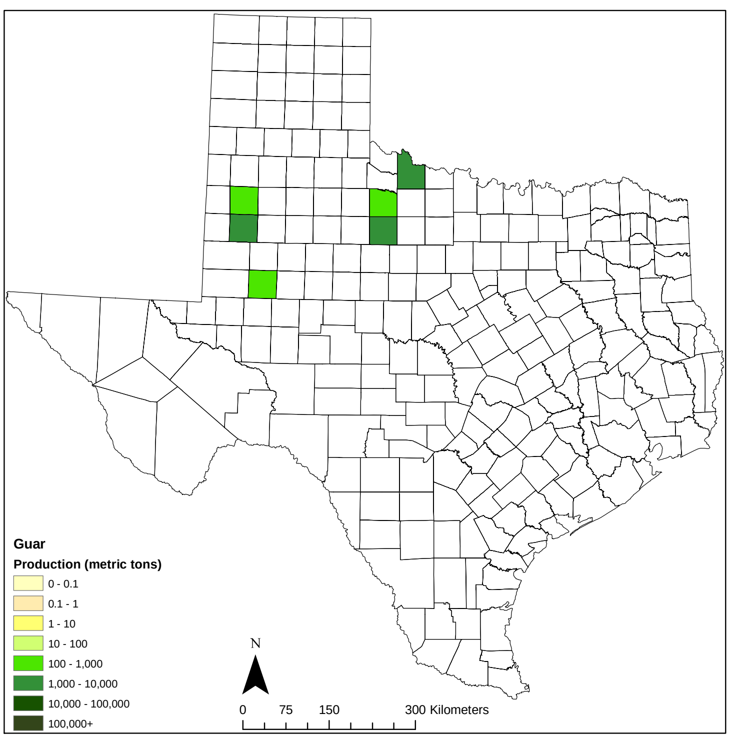

Figure C-22: Average harvested carbon from guar between 2000 and 2005.

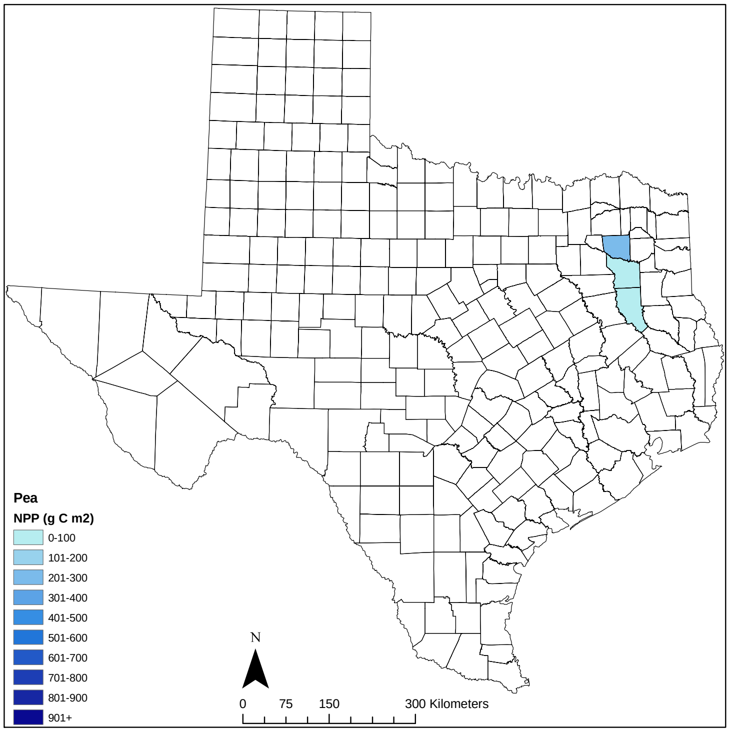

Figure C-23: Average NPP from pea between 2000 and 2005.

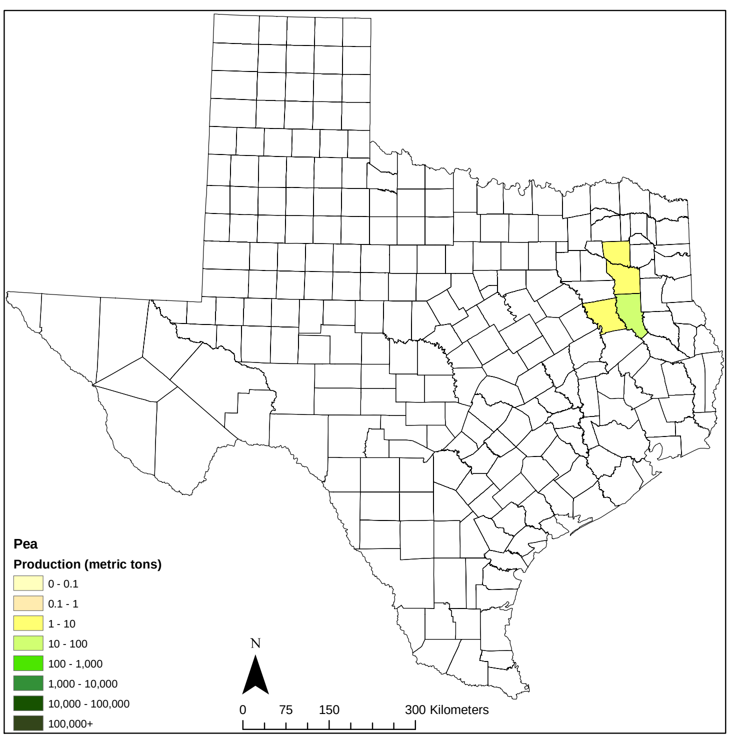

Figure C-24: Average harvested carbon from pea between 2000 and 2005.

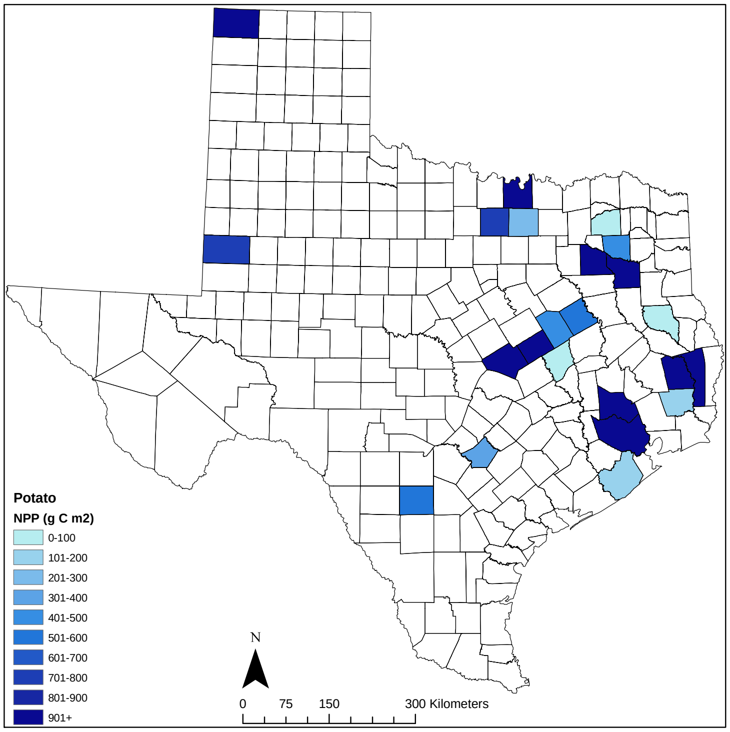

Figure C-25: Average NPP from potato between 2000 and 2005.

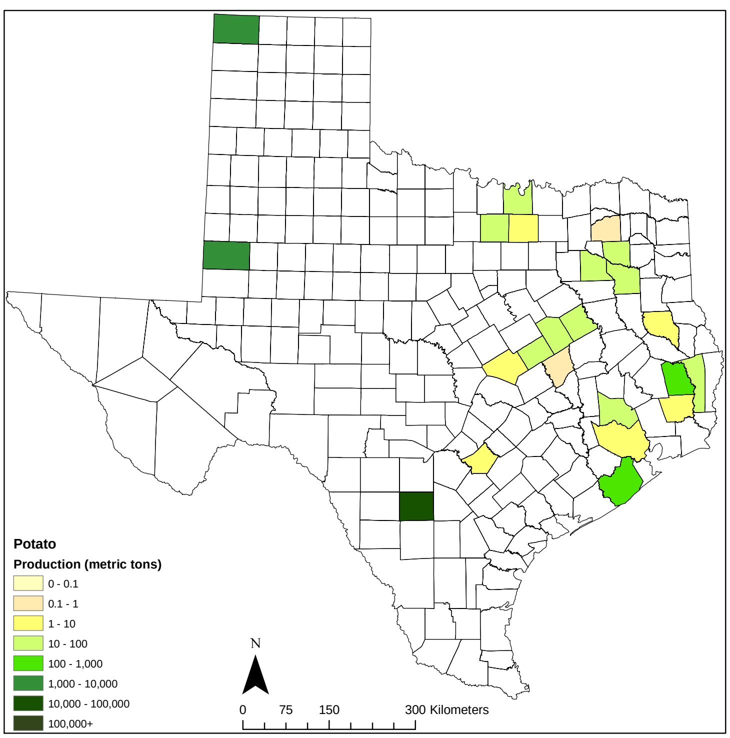

Figure C-26: Average harvested carbon from potato between 2000 and 2005.

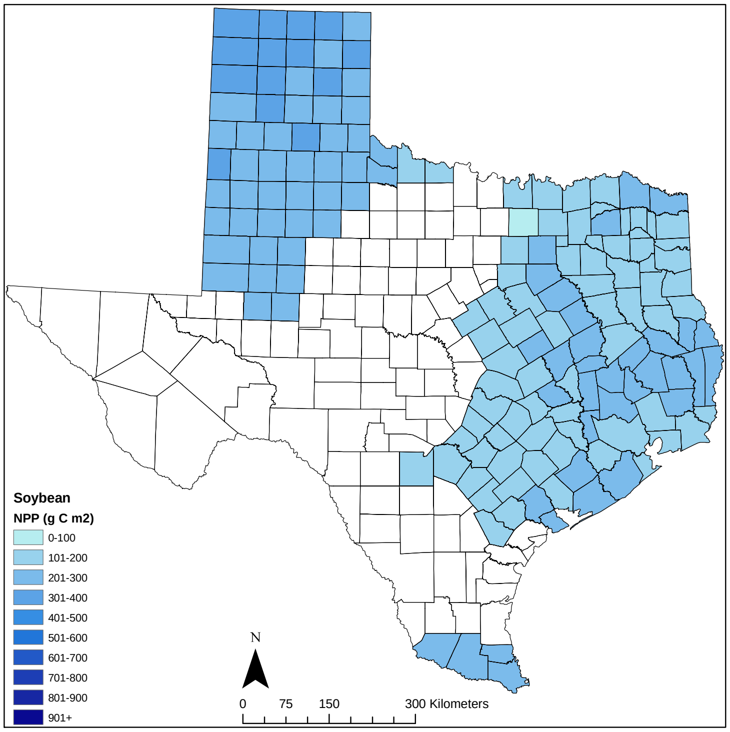

Figure C-27: Average NPP from soybean between 2000 and 2005.

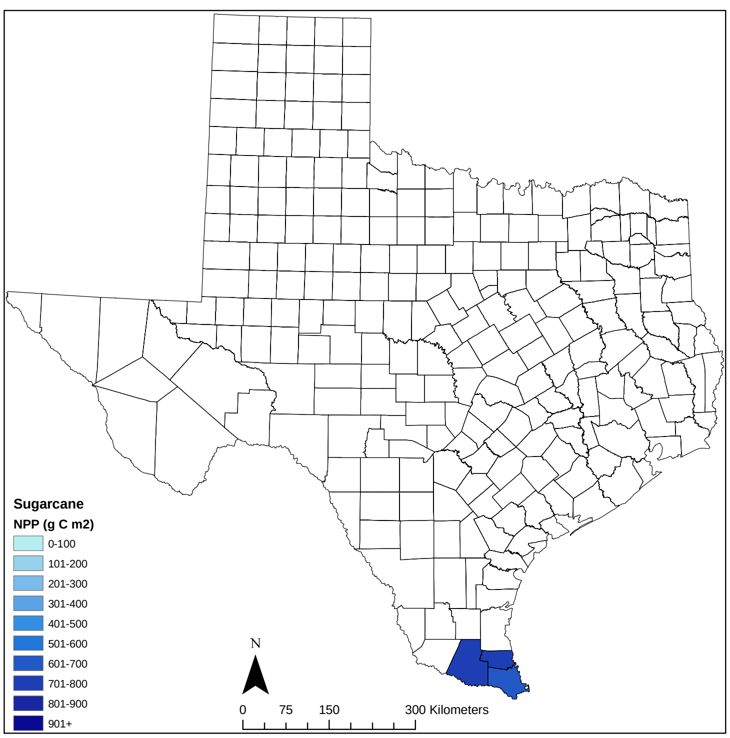

Figure C-28: Average NPP from sugarcane between 2000 and 2005.

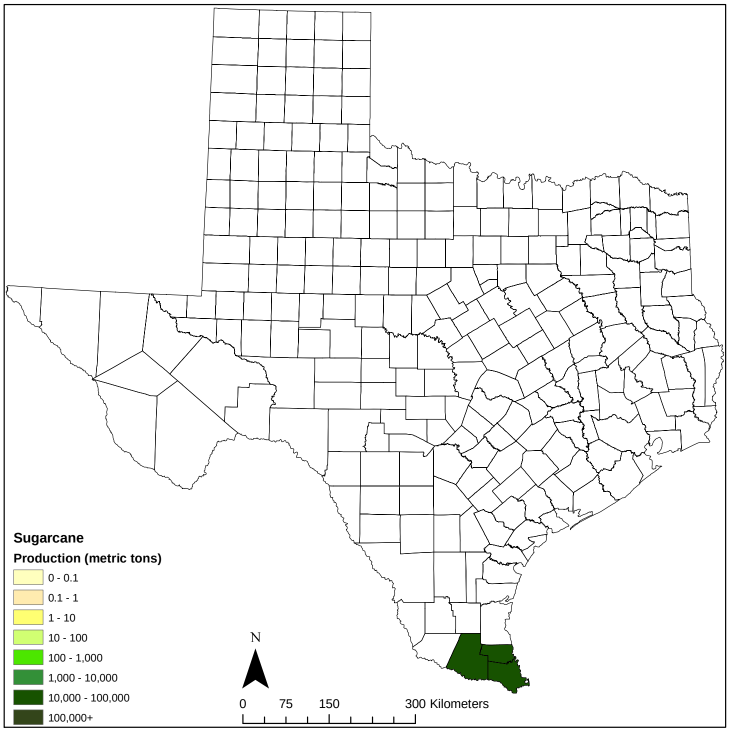

Figure C-29: Average harvested carbon from sugarcane between 2000 and 2005.

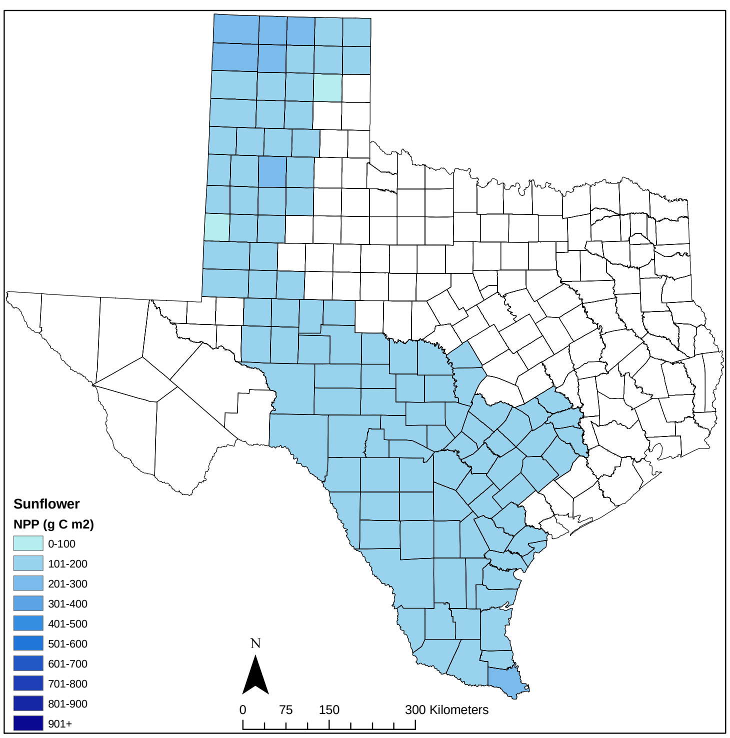

Figure C-30: Average NPP from sunflower between 2000 and 2005.

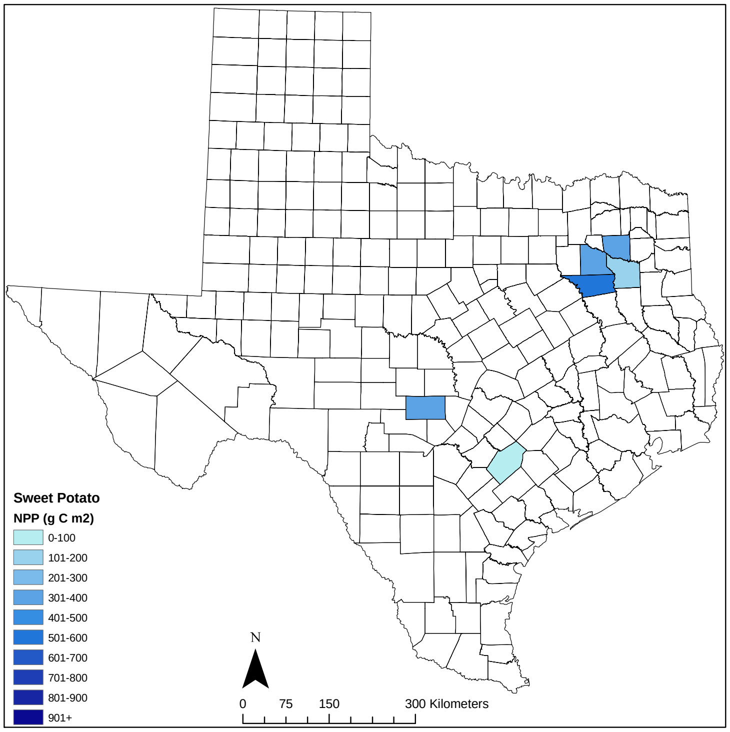

Figure C-31; Average NPP from sweet potato between 2000 and 2005.

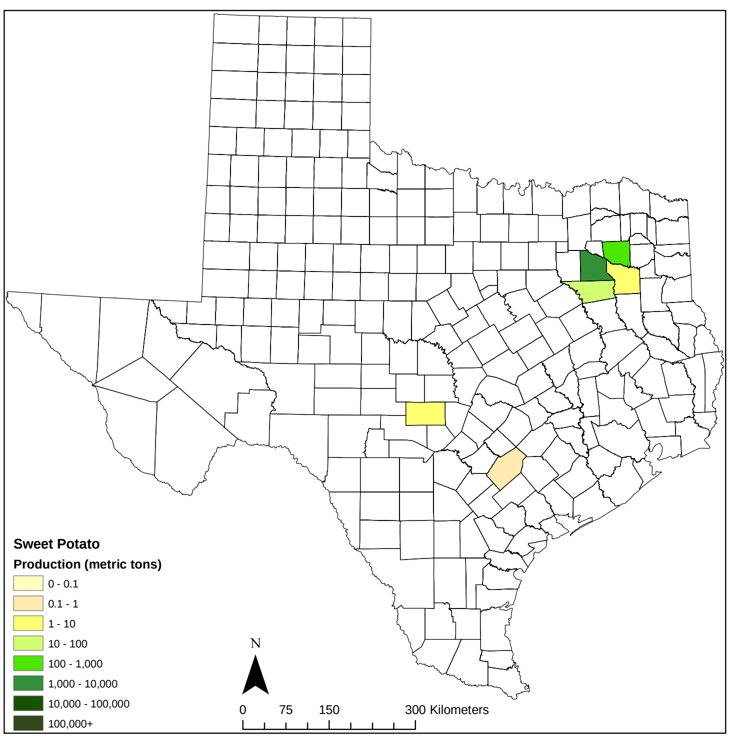

Figure C-32: Average harvested carbon from sweet potato between 2000 and 2005.

Hay and Silage

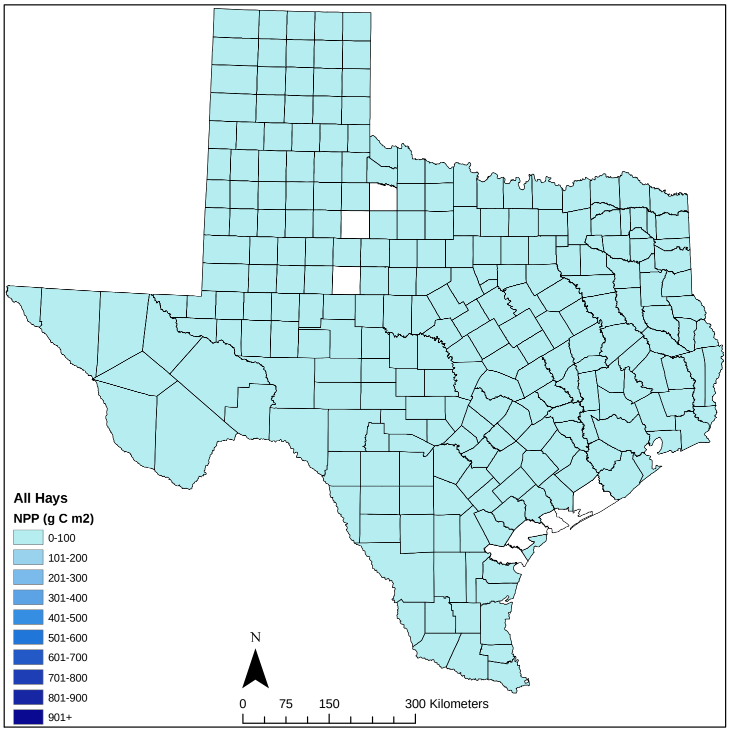

Figure C-33: Average NPP from all hay and silage between 2000 and 2005.

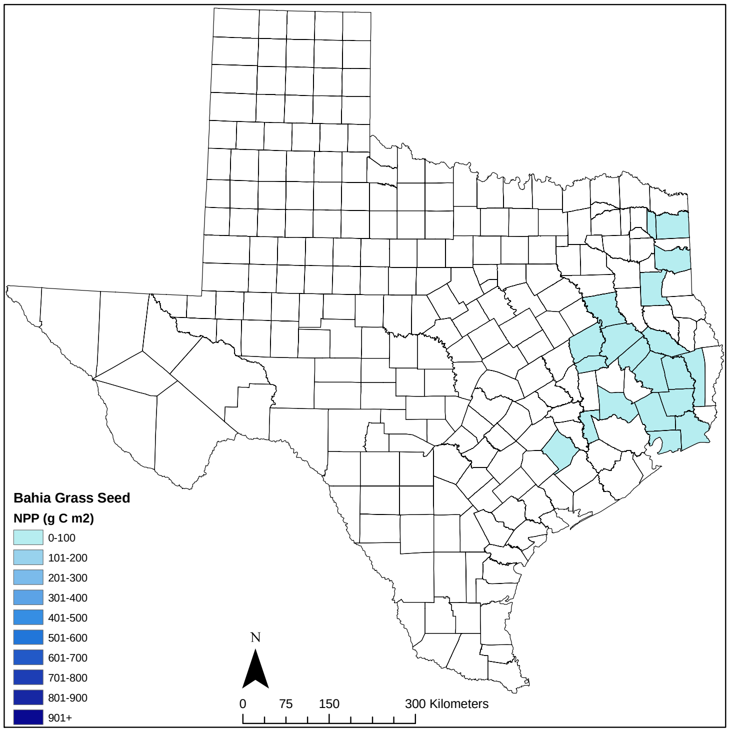

Figure C-34: Average NPP from bahia grass seed between 2000 and 2005.

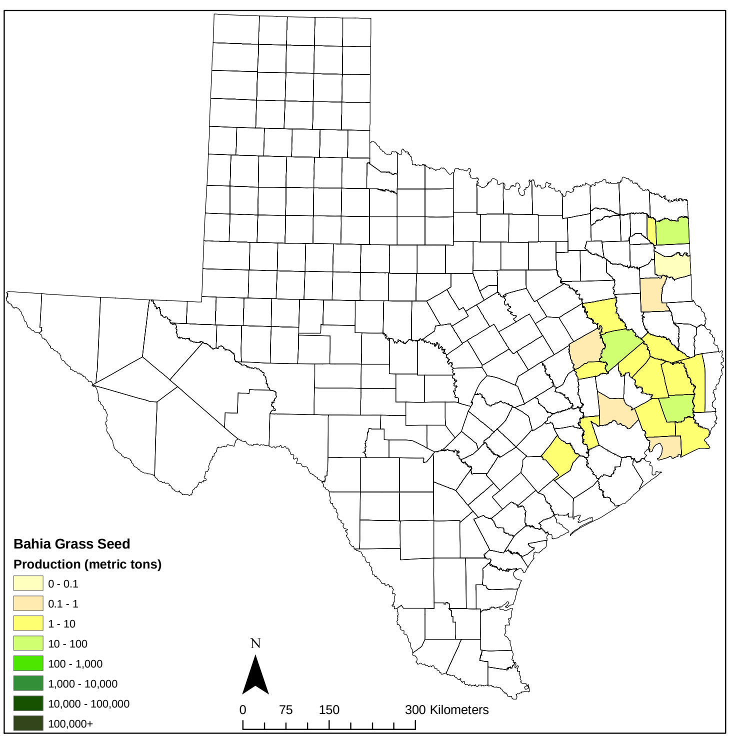

Figure C-35: Average harvested carbon from bahia grass seed between 2000 and 2005.

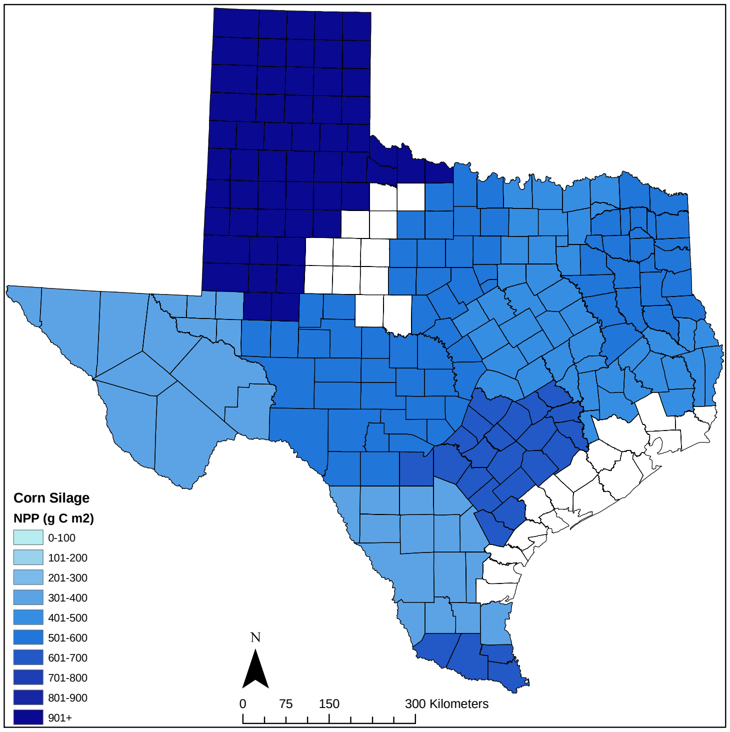

Figure C-36: Average NPP from corn for silage between 2000 and 2005.

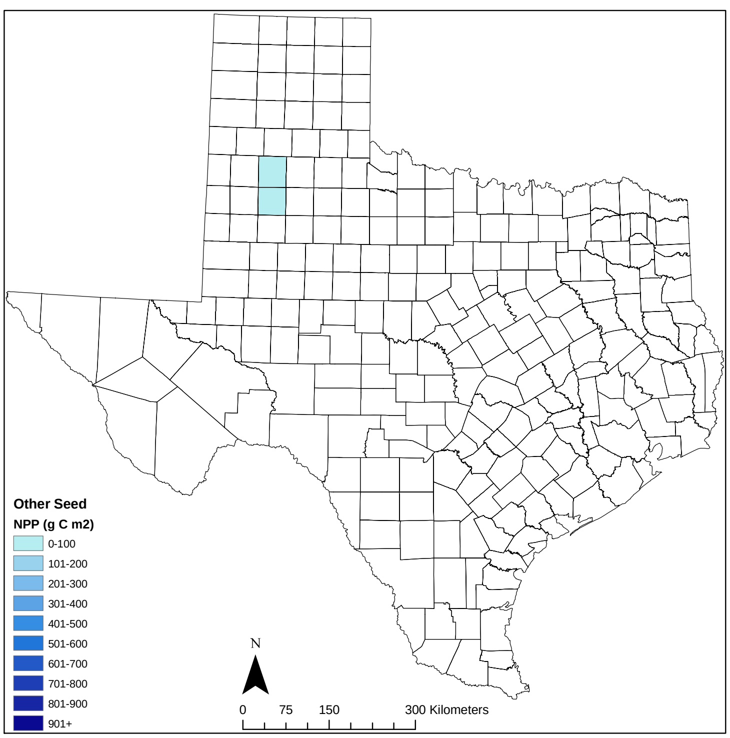

Figure C-37: Average NPP from other seeds between 2000 and 2005.

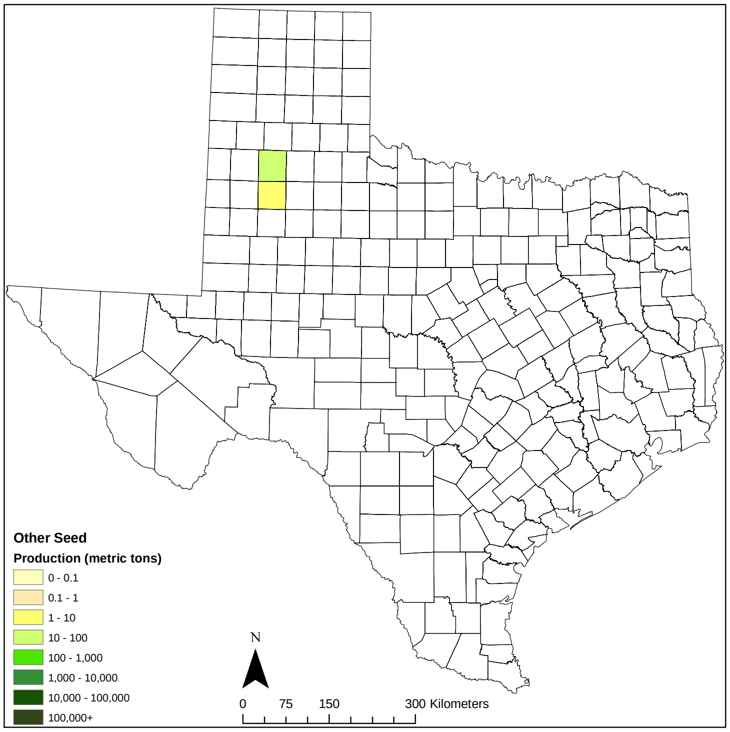

Figure C-38: Average harvested carbon from other seeds between 2000 and 2005.

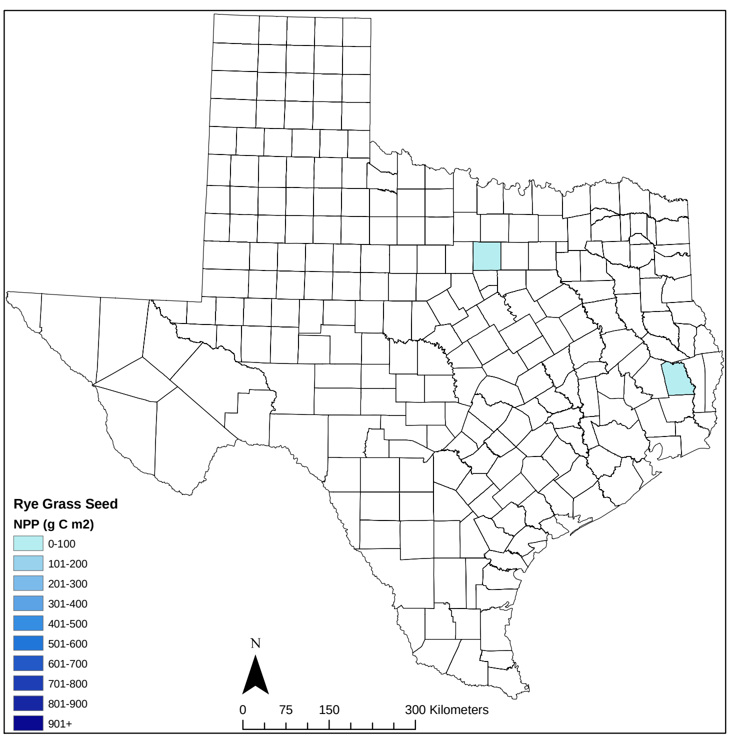

Figure C-39: Average NPP from rye grass seed between 2000 and 2005.

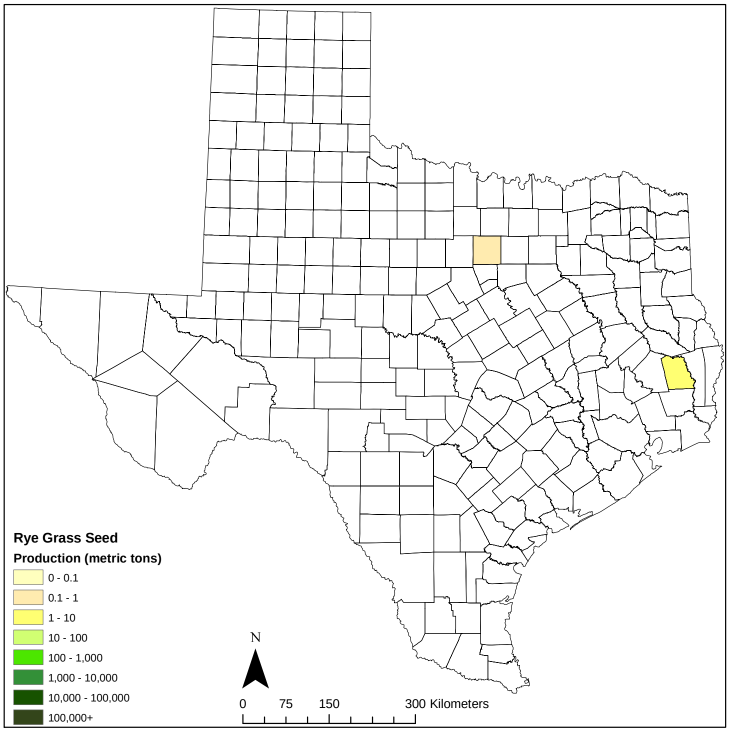

Figure C-40: Average harvested carbon from rye grass seed between 2000 and 2005.

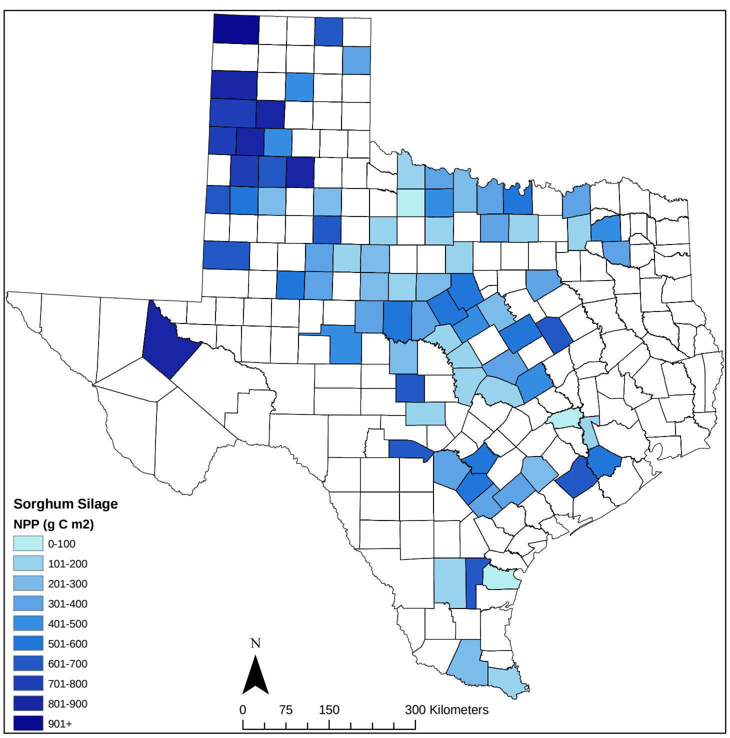

Figure C-41: Average NPP from sorghum for silage between 2000 and 2005.

Vegetables

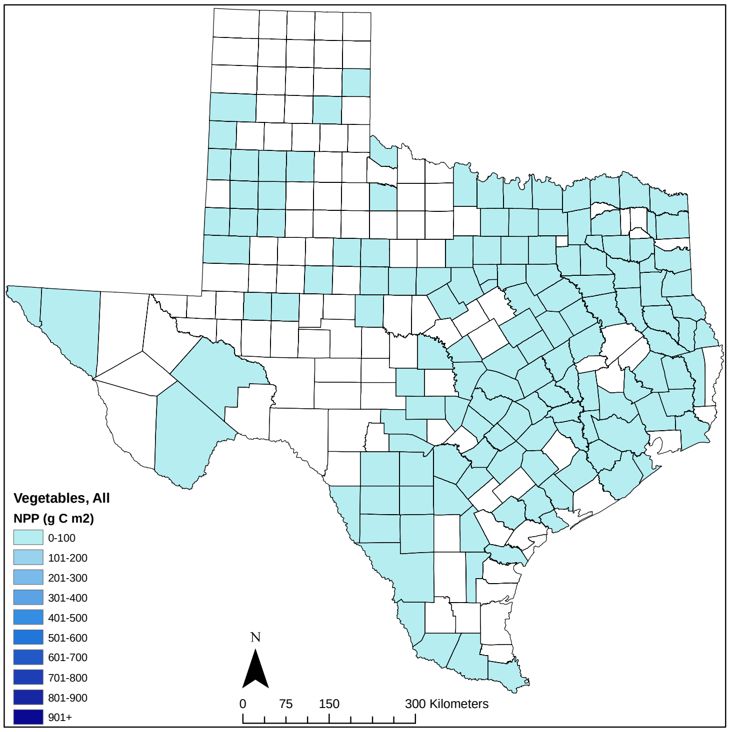

Figure C-42: Average NPP from all vegetables between 2000 and 2005.

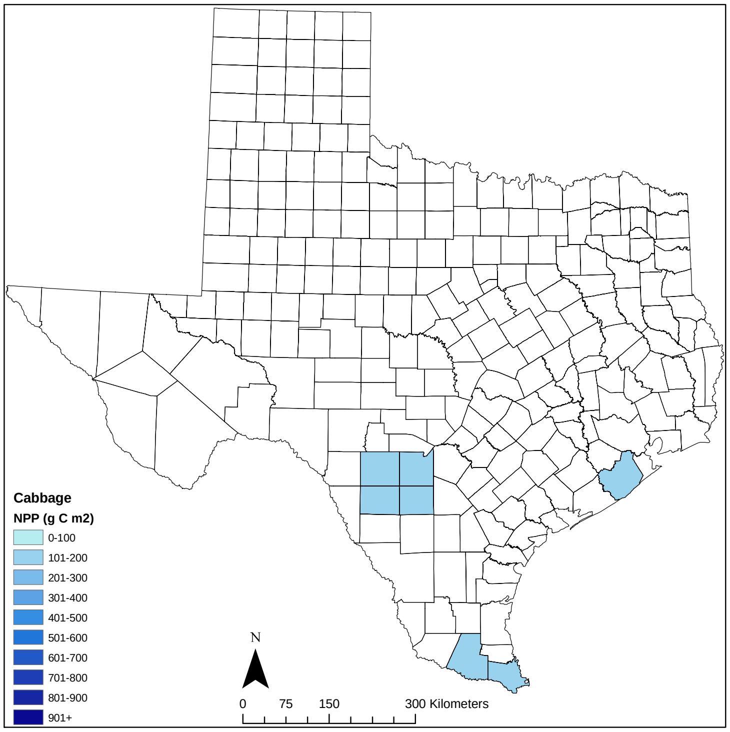

Figure C-43: Average NPP from cabbage between 2000 and 2005.

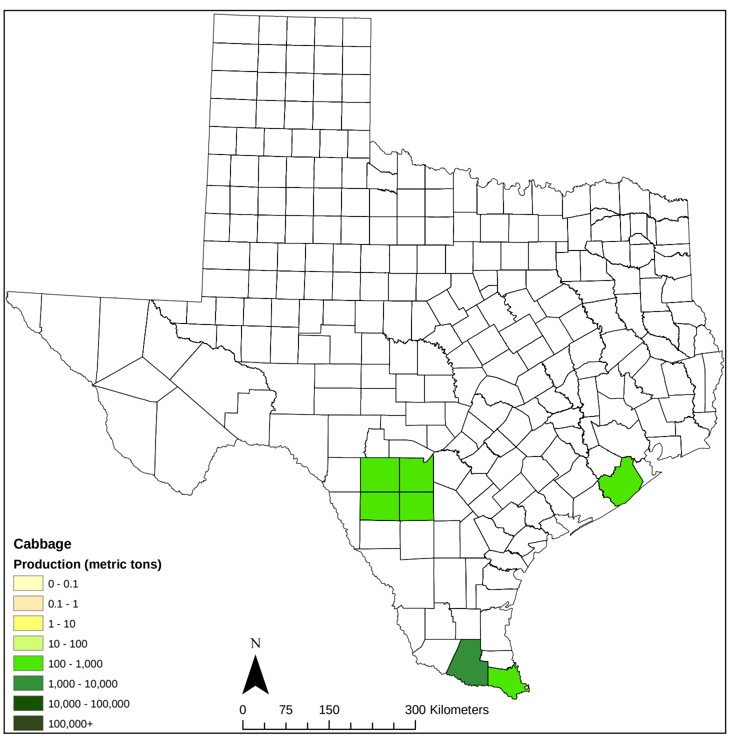

Figure C-44: Average harvested carbon from cabbage between 2000 and 2005.

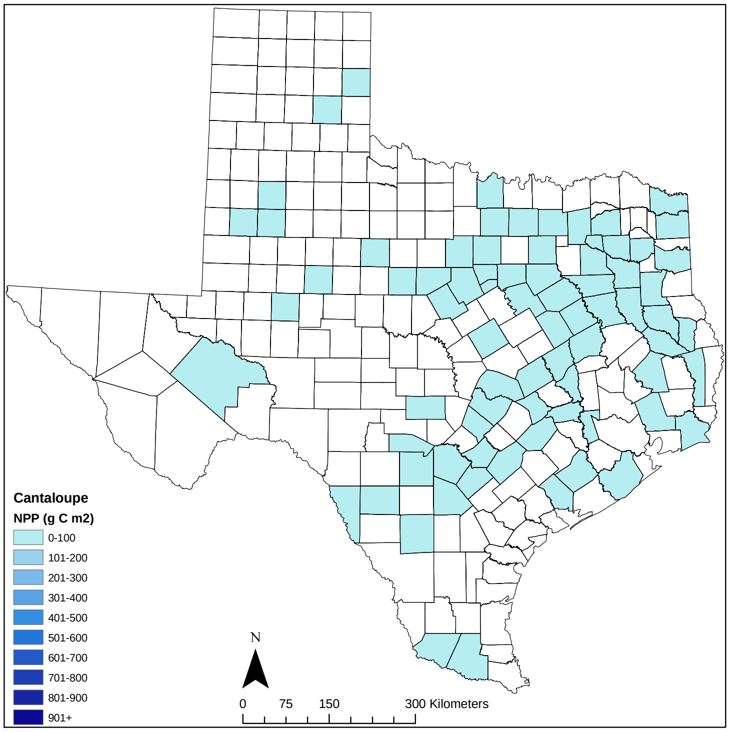

Figure C-45: Average NPP from cantaloupe between 2000 and 2005.

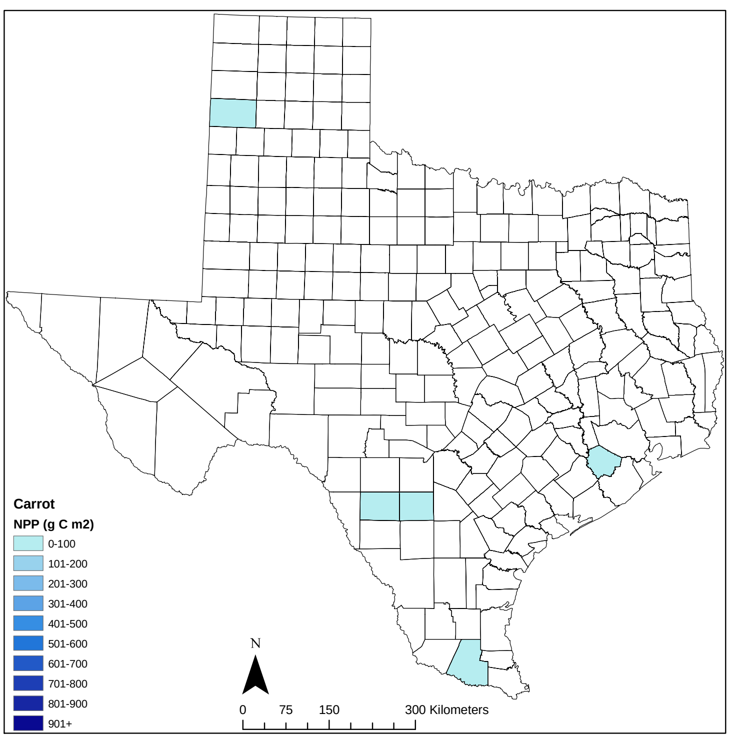

Figure C-46: Average NPP from carrot between 2000 and 2005.

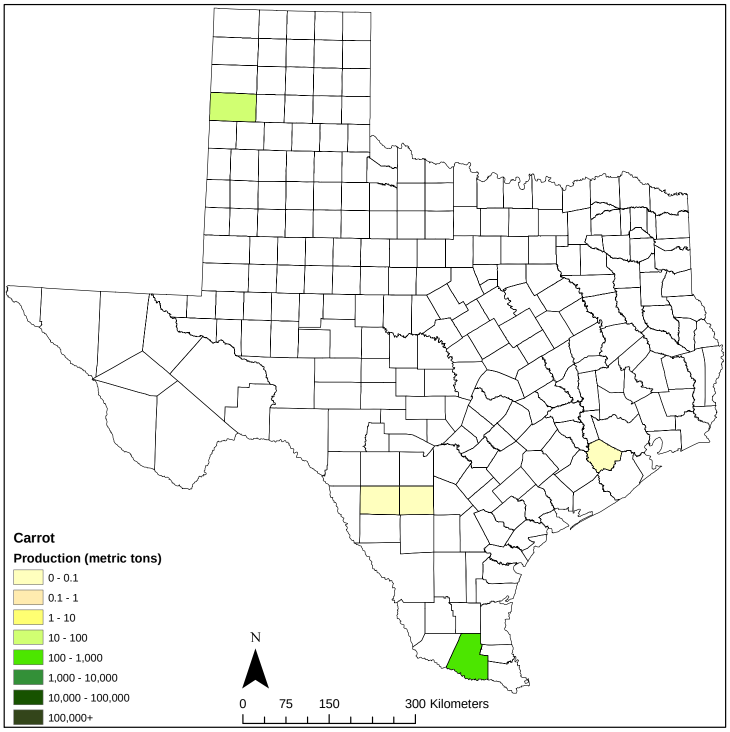

Figure C-47: Average harvested carbon from carrot between 2000 and 2005.

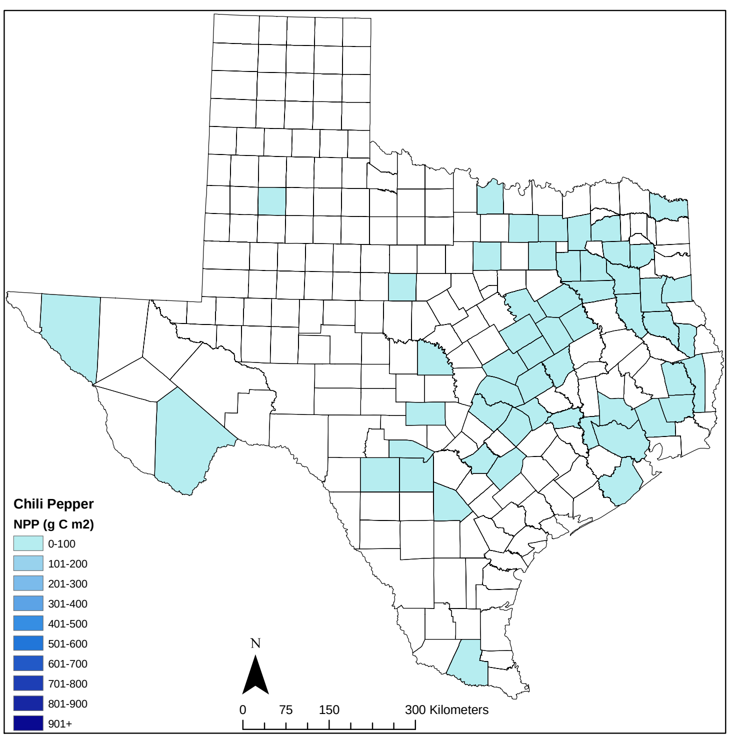

Figure C-48: Average NPP from chili pepper between 2000 and 2005.

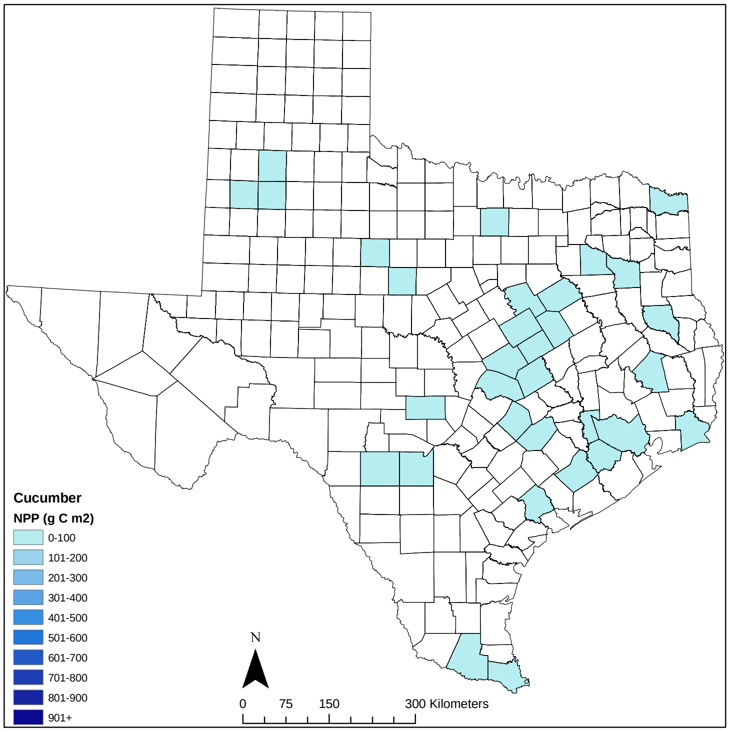

Figure C-49: Average NPP from cucumber between 2000 and 2005.

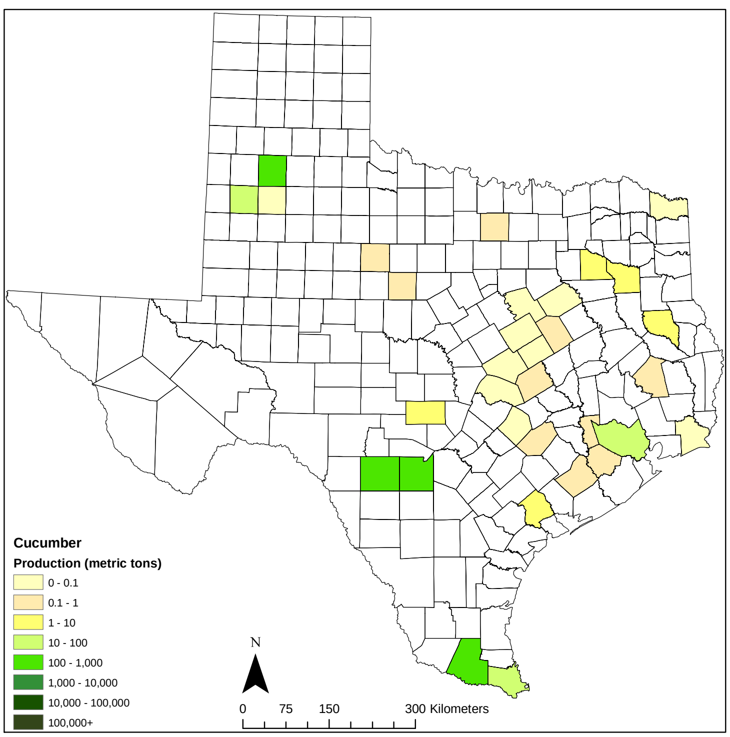

Figure C-50: Average harvested carbon from cucumber between 2000 and 2005.

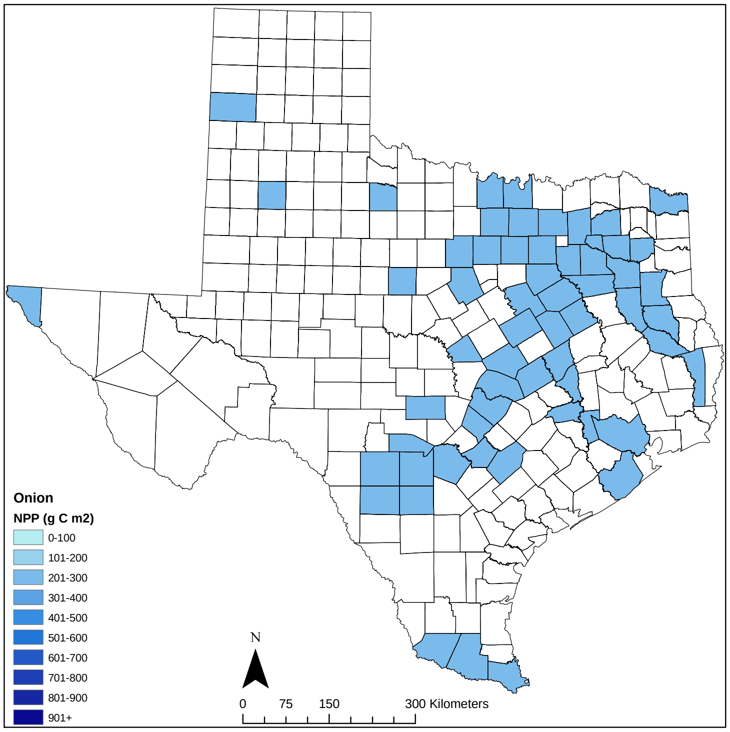

Figure C-51: Average NPP from onion between 2000 and 2005.

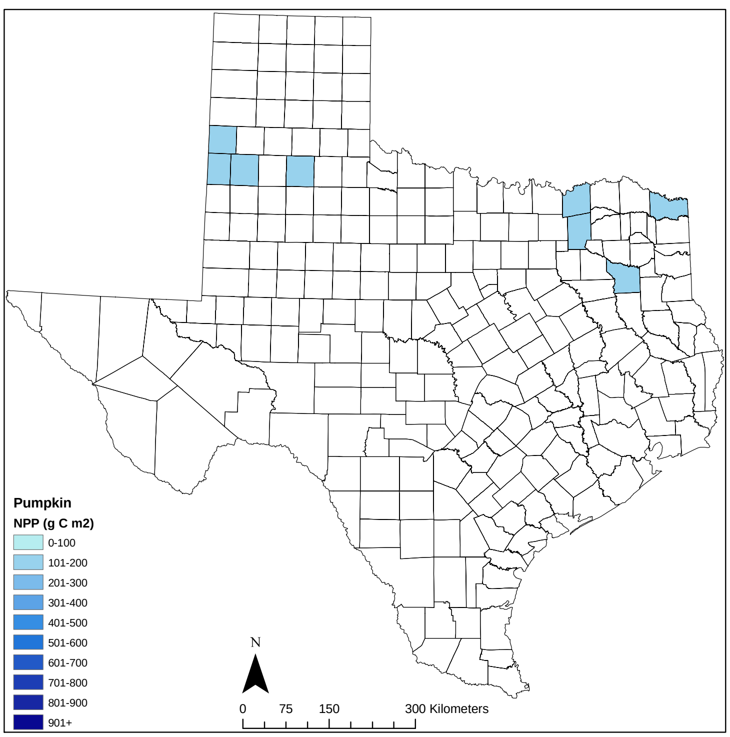

Figure C-52: Average NPP from pumpkin between 2000 and 2005.

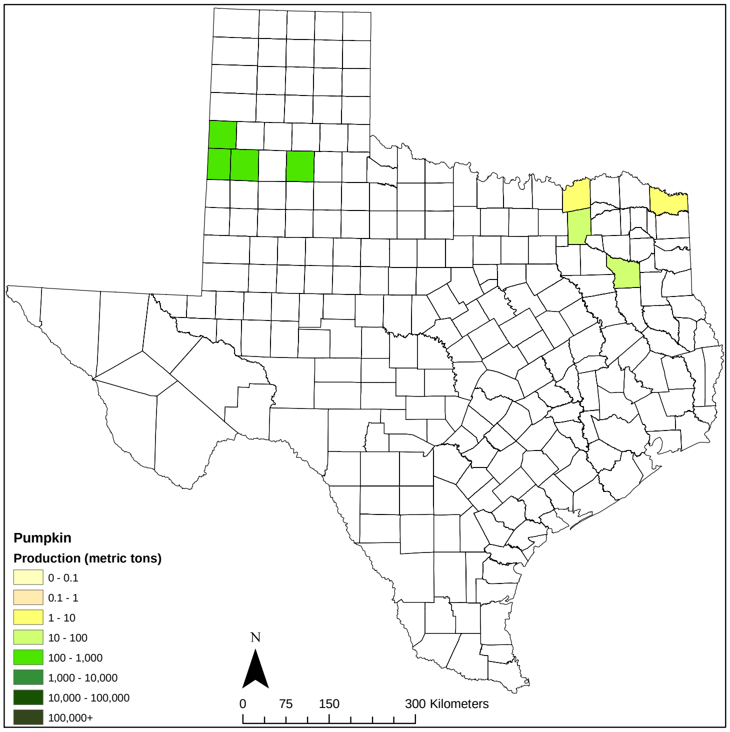

Figure C-53: Average harvested carbon from pumpkin between 2000 and 2005.

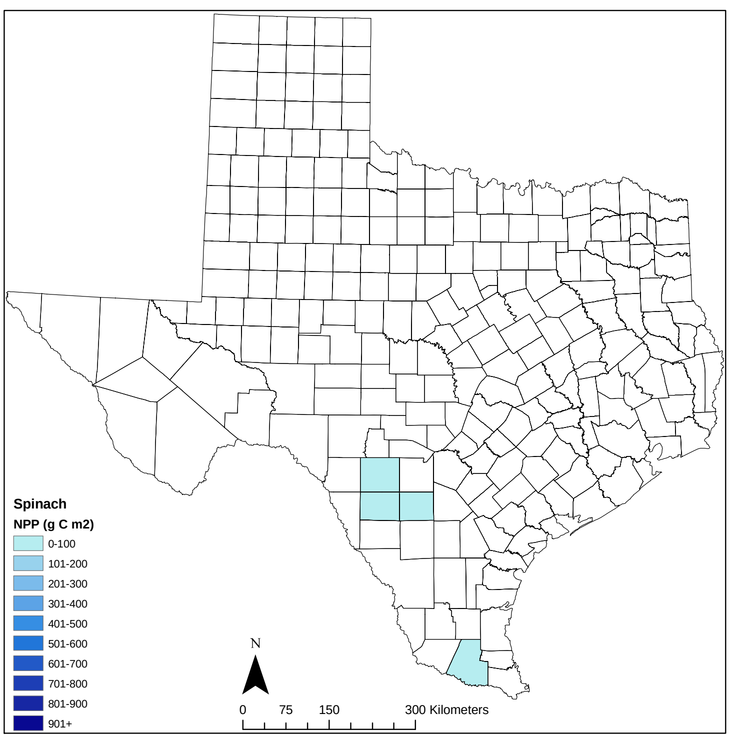

Figure C-54: Average NPP from spinach between 2000 and 2005.

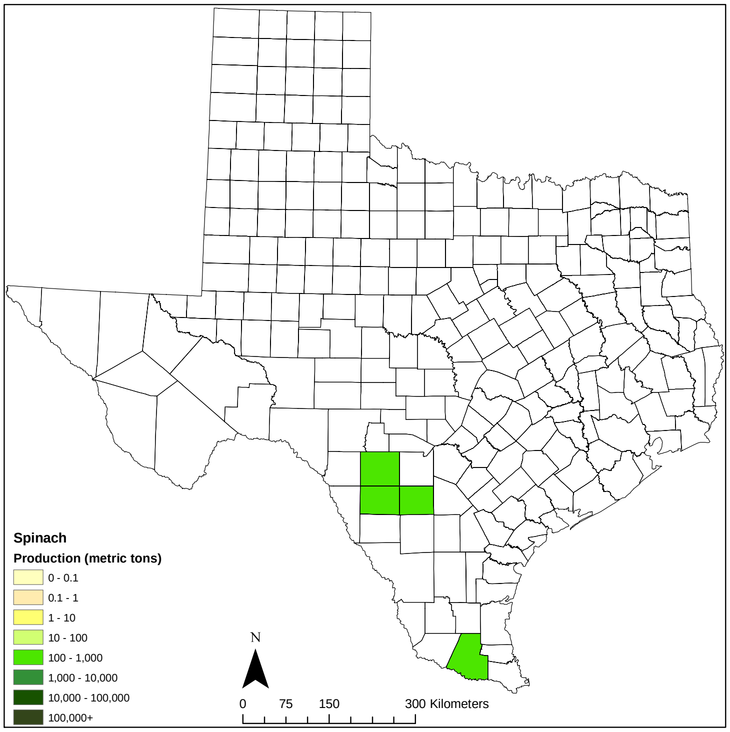

Figure C-55: Average harvested carbon from spinach between 2000 and 2005.

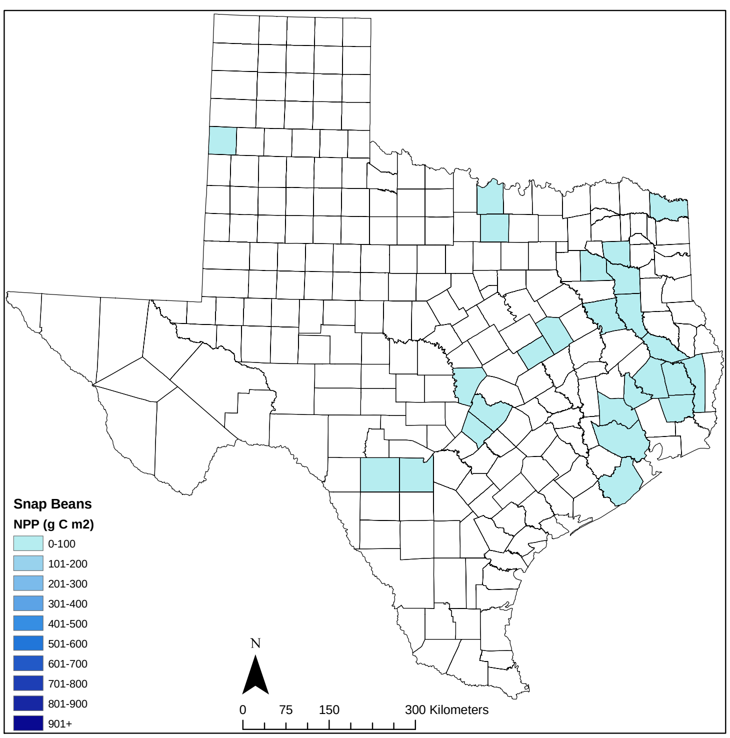

Figure C-56: Average NPP from snap bean between 2000 and 2005.

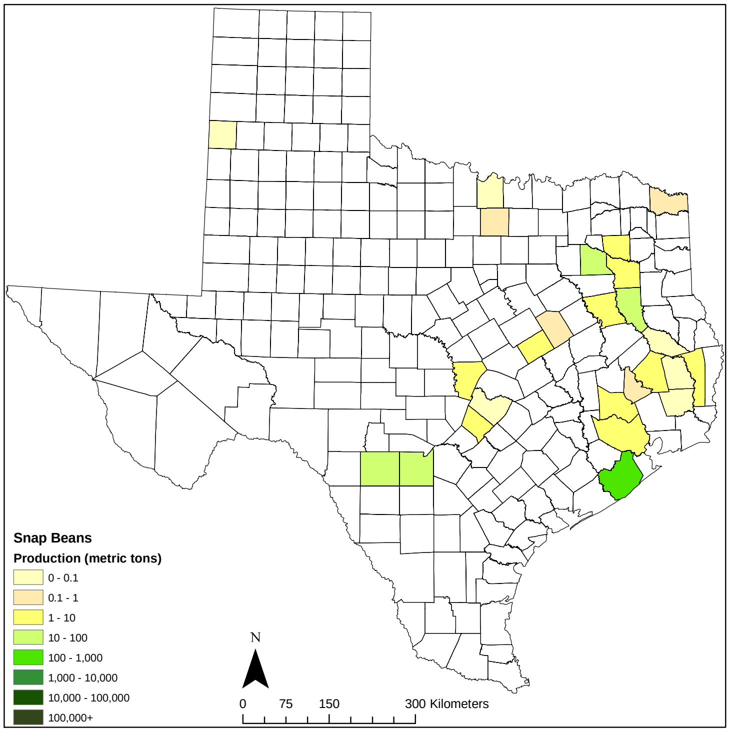

Figure C-57: Average harvested carbon from snap bean between 2000 and 2005.

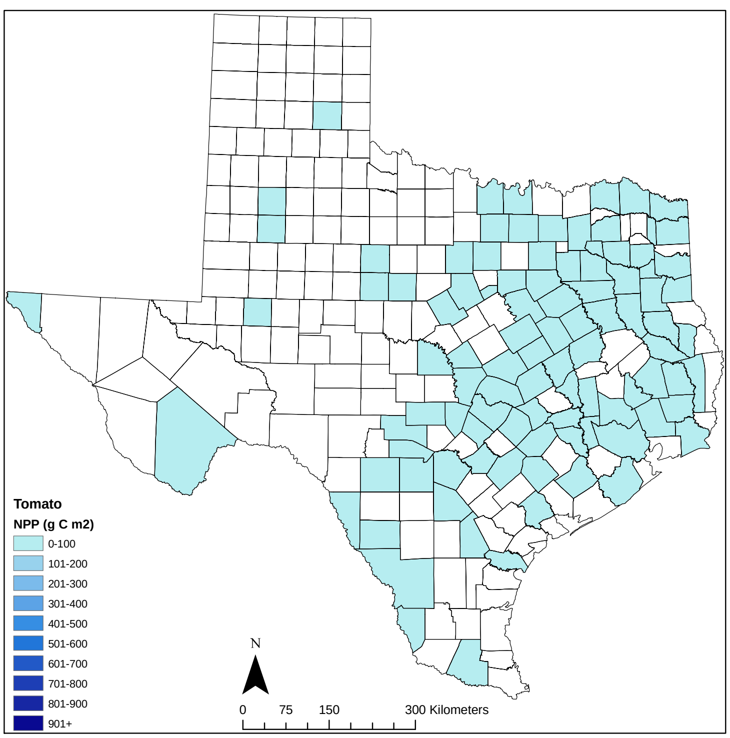

Figure C-58: Average NPP from tomato between 2000 and 2005.

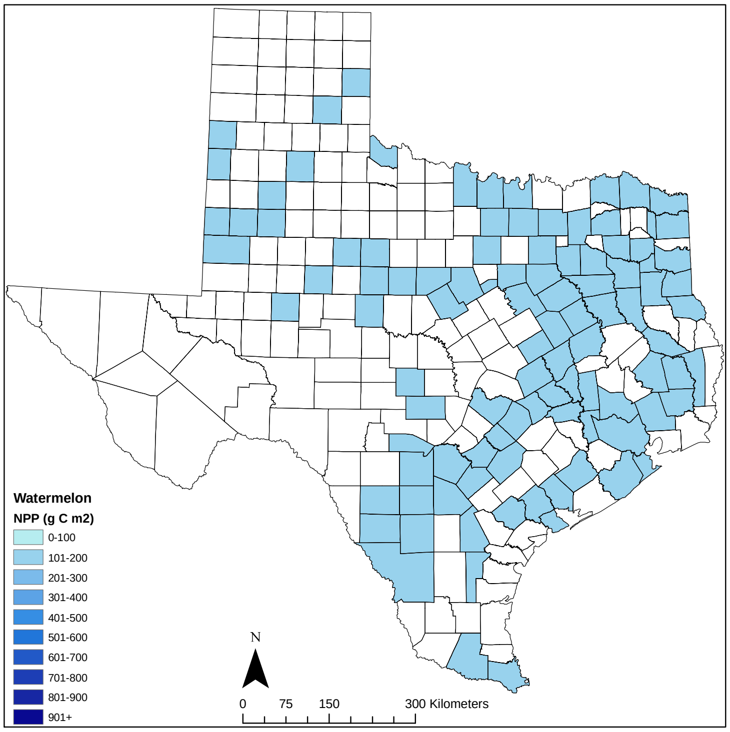

Figure C-59: Average NPP from watermelon between 2000 and 2005.

Fruit

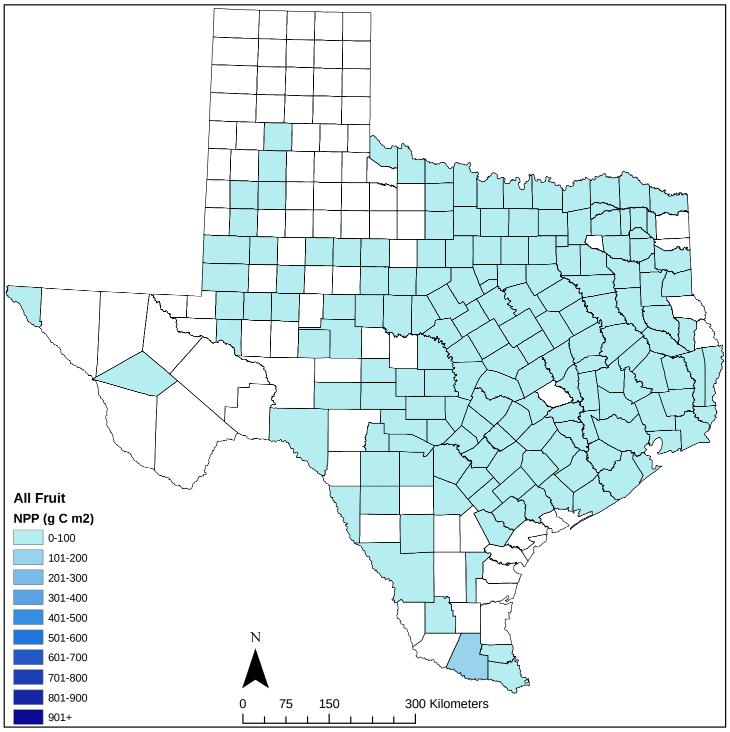

Figure C-60: Average NPP from all fruit between 2000 and 2005.

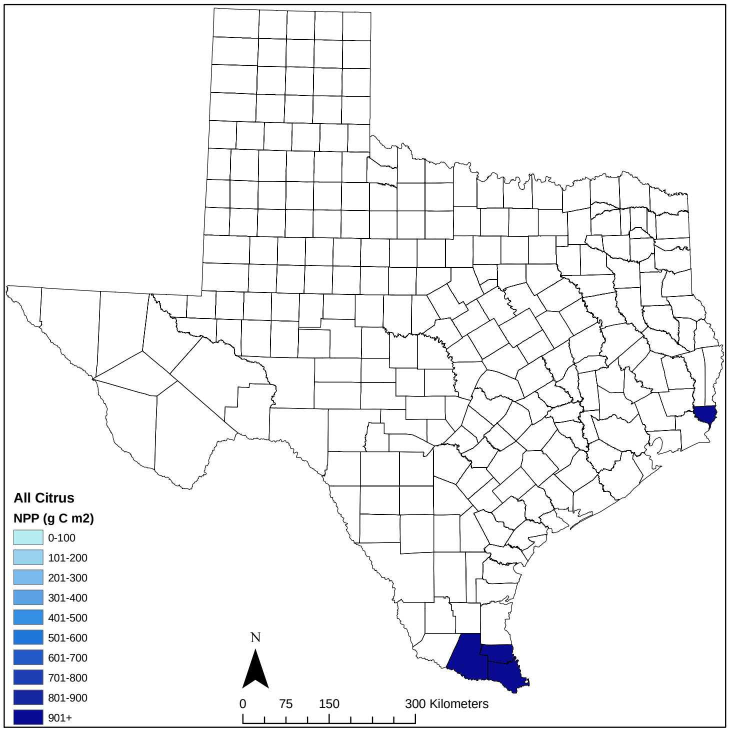

Figure C-61: Average NPP from all citrus between 2000 and 2005.

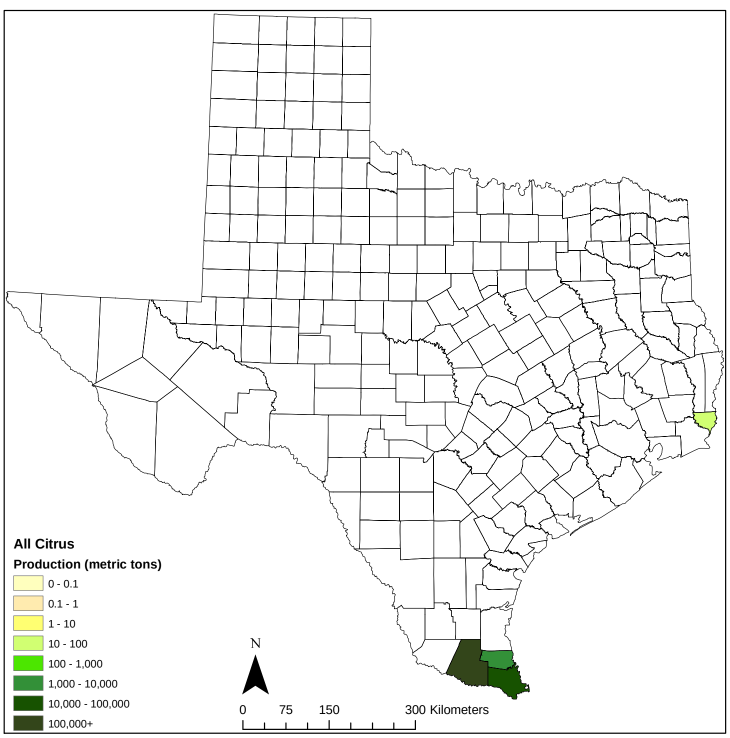

Figure C-62: Average harvested carbon from all citrus between 2000 and 2005.

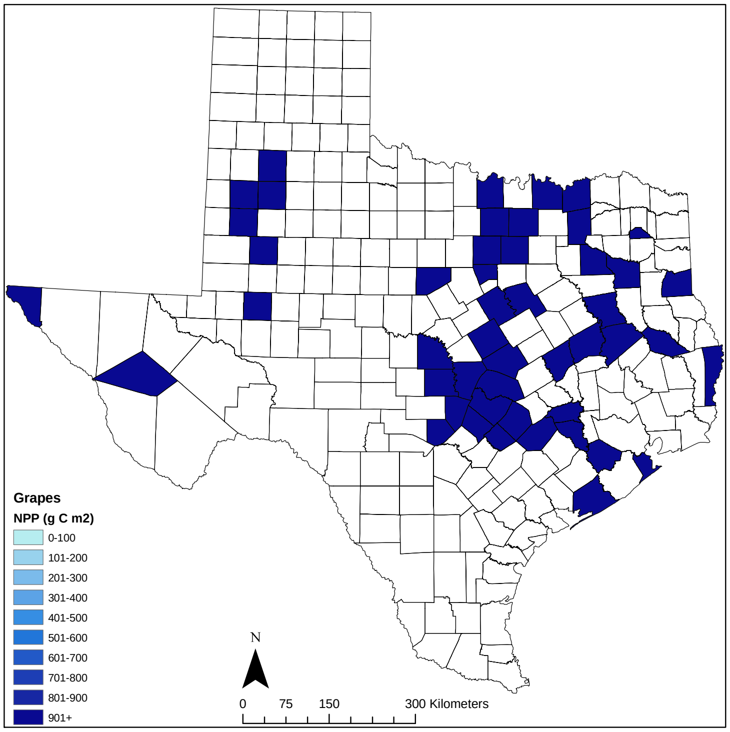

Figure C-63: Average NPP from grape between 2000 and 2005.

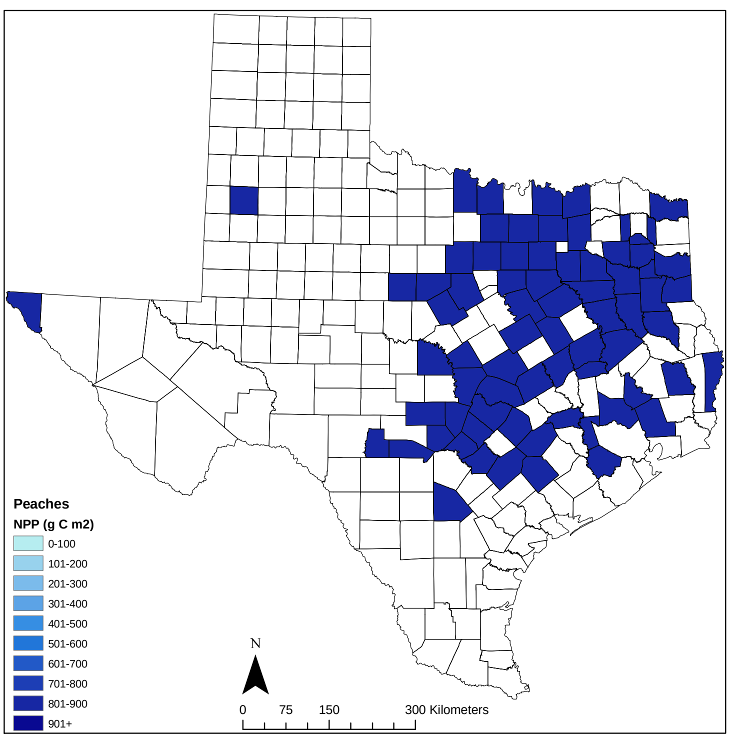

Figure C-64: Average NPP from peach between 2000 and 2005.

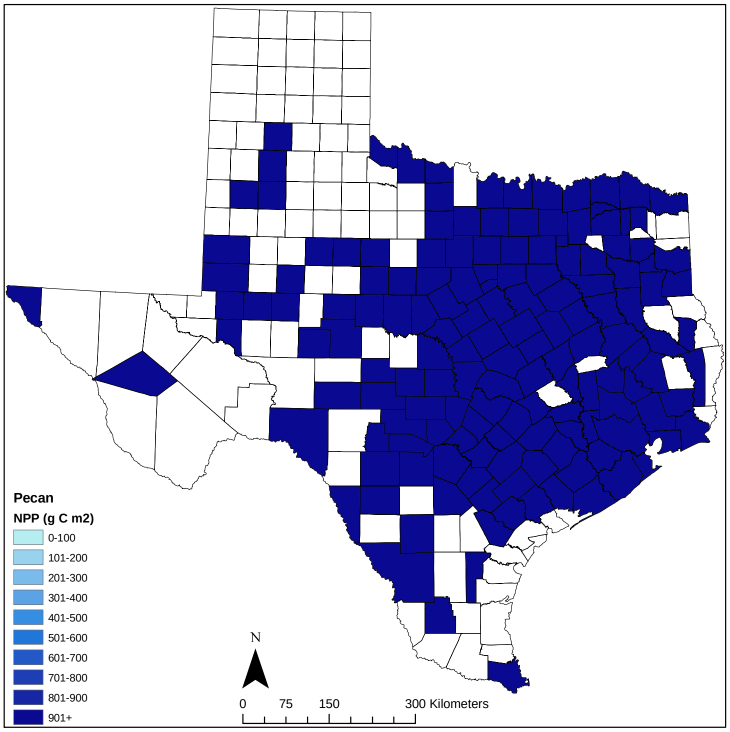

Figure C-65: Average NPP from pecan between 2000 and 2005.

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